ESSAYS IN VENTURE CAPITAL:

INSTITUTIONAL INVESTOR BEHAVIOR AND

IPO PERFORMANCE

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Abstract

This collection of essays investigates the nature of venture capital as an asset and as a financer of industry. Chapter 1 presents an overview of venture capital, starting with its history and development. It examines the nature of venture capital and its ability to generate returns for its investors with emphasis on data sources available. Using a simple model, this chapter predicts that the inclusion of venture capital will improve the mean-variance frontier of an investor’s portfolio. Chapter 2 takes a closer look at these investors in venture capital, known as limited partners. Here I investigate the behavior of the limited partners with respect to their private equity investments. This chapter models the rationale for the common practice of syndication of the investment partnership interests. While Chapter 2 focuses on the “parents” of venture capital, Chapter 3 observes the performance and survivability of some of venture capital’s offspring—initial public offerings of the companies financed by venture capitalists. A major finding of this analysis is that venture capital firms which specialize by industry produce initial public offerings which tend to survive longer, perform better, and are less likely to delist. Chapter 3 also introduces a new dataset to the field of private equity research.
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CHAPTER 1: THE STATE OF VENTURE CAPITAL

Abstract

This collection of essays investigates the nature of venture capital as an asset and as a
financer of industry. Chapter 1 presents an overview of venture capital, starting with its
history and development. It examines the nature of venture capital and its ability to
generate returns for its investors with emphasis on data sources available. Using a simple
model, this chapter predicts that the inclusion of venture capital will improve the mean-
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partners with respect to their private equity investments. This chapter models the rationale
for the common practice of syndication of the investment partnership interests. While
Chapter 2 focuses on the “parents” of venture capital, Chapter 3 observes the performance
and survivability of some of venture capital’s offspring—initial public offerings of the
companies financed by venture capitalists. A major finding of this analysis is that venture
capital firms which specialize by industry produce initial public offerings which tend to
survive longer, perform better, and are less likely to delist. Chapter 3 also introduces a new
dataset to the field of private equity research.
1.1 Introduction-- The Nature of Venture Capital

This chapter reviews the structure, history and development of venture capital as both an investment vehicle and an asset class. It begins with a presentation of the venture capital (VC) cycle, from fund inception through staged financing and fund liquidation. It then reviews a series of landmarks which serve as catalysts for its evolution. In addition, this chapter discusses venture capital data sources, biases in reporting and recent breakthroughs in benchmarking of VC. This chapter then presents a simple model of the effect of VC investments on an institutional investor’s mean-variance frontier. Finally, this chapter investigates the most recent academic developments in venture capital and serves as a foundation for the subsequent chapters of this doctoral thesis.

1.1.1 The Venture Capital Firm

Venture capital firms invest in small, young firms with high levels of uncertainty; typically small start-up entrepreneurs. Its place as a subclass of private equity implies that venture capital takes strictly equity positions. In addition to equity financing the VC firm will provide the start-up with suggestions for operational improvements and often takes one or more seats on the new firm’s board of directors.

An excellent exposition on the organization of the venture capital firm comes from Sahlman (1990). This study contrasts the structure of the venture capital (VC) with that of a public corporation. Sahlman shows that the basic construct used by the venture capitalist in
both acquiring capital and investing in entrepreneurs is the contract. According to Sahlman, on both the sell-side (fundraising from institutions) and the buy-side (investing in entrepreneurs) the contract addresses three of the primary problems associated with private equity: the sorting problem, agency issues and operating-cost matters.

The venture capital firm is typically set up as a limited liability partnership (or limited partnership) to afford its partners the benefits of limited liability. Its intent is to commit capital to young start-up firms. This is accomplished by raising one or more funds. The fund itself is the vehicle that allows capital that is raised to be allocated to entrepreneurs. The fund is also the mechanism by which the firm monitors the individual investments and grows the start-up firms, always with an eye towards exit from the initial investment. The general partners control the activities of the fund, raise the fund and develop exit strategies. The limited partners provide primarily financing.

Venture capital firms have a variety of goals and levels of expertise. Oftentimes a firm will focus on one particular industry. For example, Alpine Technologies is a venture capital firm which invests only in companies within the field (albeit broad) of information technology. Conversely, Boston based General Catalyst, while generally focused on high technology, is not committed to just one high-tech industry. It will invest in healthcare, pharmaceuticals, biotechnology and information technology. While many venture capital firms focus solely on high-technology, there are some VCs who are agnostic towards the technology level of their portfolio companies.
Venture capital firms can be regional or national in scope (rarely would a venture capitalist be classified as international given that the dense legal contracts necessary for commitment are constrained by national boundaries). As of 2011, the center of the venture capital universe is still Silicon Valley. California, with both Silicon Valley and the LA area, contains the strongest presence of venture capital of any state. New York, Massachusetts (with the vibrant Boston-based venture capital), Texas, Maryland and Pennsylvania follow as the largest repositories of venture capital activity.

1.1.2 Limited Partners: Venture Capital’s Progenitors

Investments in venture capital come from a set of standard sources. Those who commit capital act as limited partners, providing limited advice and consent. The very definition of a limited partner, within the context of the venture capital firm, implies that the investors are limited in their ability to directly control the capital they commit. During the fundraising process, the limited partner and the venture capital firm will decide on size of committed capital. In most cases, the venture capitalists themselves will invest a percentage of their own capital into each of the funds. The rationale for this is two-fold. First, it is to signal an alignment of interest to potential limited partners and therefore alleviate many of the agency problems associated with private equity. Second, self-committed capital has the tax advantages of timing the tax liability as well as historically lower capital gains rates.
The capital commitment from the general partners is typically a small portion of the overall target fund size, usually around 1%. The vast majority of the money comes from outside sources, the limited partners. The lifespan of a venture capital fund is typically 10 years (though some funds can opt for longer life\(^1\)). Capital committed will be drawn down by the general partners in the first one to three years as the general partners select worthy entrepreneurs. Typically, the investment is recorded at cost until the exits (such as the sale of an entrepreneur to another company) occur. Thus, on the books of the fund, there is a long-run focus to any venture capital commitment.

To this end, most investors in venture capital are institutional investors. These institutional investors include endowments, pension funds and foundations. The long-run focus of these institutions matches well with what is, by definition, a long-run relatively illiquid investment. An endowment, for example, has an indefinite (hopefully infinite) lifespan. Constrained by both prudence and the need to subsidize yearly university expenditures, endowments need to grow (and typically at a rate well-above CPI, since historically the cost of higher education, measured by the Higher Education Price Index, has outpaced inflation.\(^2\)

The desire for long-run growth gives many endowments an appetite for venture capital. For endowments with access to the most successful venture capitalists, this translates into

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\(^1\) For example, an evergreen fund channels returns generated by its investments back into the fund itself. This goal provides a continuous capital supply.

\(^2\) The Higher Education Price Index, compiled by the Commonfund has tracked about 120 basis points higher than the CPI (historical arithmetic means of 4.4% vs. 3.2%).
higher expected returns (see Sections 1.3 and 1.4). Even with no access to Kleiner-Perkins, Sequoia, General Catalyst and the other best-in-class VCs, venture capital can provide a means of diversification outside of the traditional asset classes.

The limited partner’s relationship with the venture capitalist begins with capital fundraising. The VC general partners (and sometimes a marketing agent) will meet with investment officers from the institutional investor. The general partners will present the size and goals of the fund. The venture capital (business) plan will also outline past fund performance (if applicable), management experience and expertise and some terms and conditions (such as management and performance fees). Typically, the limited partner (LP) will conduct its own due diligence. Often, the potential LP will contact other limited partners that have worked with this venture capitalist to assess the relative strength of the fund. Chapter 2 of this dissertation discusses some of the reasons for information sharing and possible syndication among the limited partners. Due diligence aside, the relative prestige of the institution against the expected performance of the fund typically determines how the meeting is conducted. For example, there is a vast difference between Harvard Management Company committing capital to a new, unknown venture capitalist or a small college looking to gain access to Kleiner-Perkins.

If the due diligence proceeds positively, contracts will outline the terms and conditions of the capital commitment. Here management fees are agreed upon—typically 2% of committed capital. The contract will also explicitly define the rate of carried interest. Carried interest is the share of profits that the general partner earns on any profits above
committed capital. Carried interest helps decrease the principal-agent problem by aligning the incentives of the agents (the general partners) with the interest of the principals (the LPs). Carried interest earned is often reinvested by the GP into the fund (or future funds) so that when finally realized, the income is treated as capital gains. Typical carried interest rates are 20%, though some of the more prestigious venture capital funds will ask for 25% (or more, notably in the late 1990s during the technology boom).

The terms of commitment can become even more complex when contingencies such as preferred returns, clawbacks and catch-up are added. If a preferred return (sometimes referred to as a hurdle rate) is stated, then the limited partners must achieve that rate of return annually on their committed capital (say 8% or 10%) before any carried interest is transferred to the general partners.

Typically a preferred return is coupled with a catch-up rate which states that once the preferred return is achieved, any additional profits are distributed at a rate greater than the explicit carried interest rate until the general partner “catches up” to the percentage implied by the carried interest rate on all profits. If carried interest is 20%, then the catch-up could, in theory be any percent greater than 20% (but less than 100%, of course). Most catch-up rates are significantly higher than the carried interest rate to allow the general partner to make up on lost carried interest. The catch up continues until the carried interest allocation is reached. A clawback provision is used to ensure that the general partners do not earn more than the carried interest states. This would typically occur if a portfolio company, which was expected to do well (and previously experienced no write-down), is suddenly
written down or written off. The overall rate of return earned by the general partners against the fallen overall value of the fund may increase above the carried interest agreed to by the limited partnership. The limited partners may “claw back” any overage that occurs.

Once the limited partners agree to the terms and conditions of the commitment, the general partners will begin to “source deals,” that is, to invest in a variety of start-up companies. The capital committed by the limited partners will be drawn down—requested by and delivered to the general partnership. This will occur during the first several years of the fund’s lifespan, which is typically set at 10 years.

1.1.3 The Venture Capital Cycle

There are typically four stages in the life of a venture capital fund. As discussed in the previous section, the first stage is fundraising. This will occur six months to a year prior to active investing. The general partners will contact one or more limited partners that have interests which will align with the goals of the fund. Once the target fund size is reached, the fundraising process is complete. The year in which the VC fund begins actively sourcing deals is known as its vintage year. Please see Figure 1 for the venture capital fund’s life cycle as it relates to time and fund size.

The second stage of the venture capital fund is the sourcing, due diligence, and investment in portfolio companies. This second stage typically occurs in the first three to five years (sometimes as long as six years). When a VC firm “sources” an entrepreneur, the
entrepreneur has been brought to the attention of the general partner. Sourcing can occur through multiple means: Venture capital specialists often rely heavily on trade press and trade shows. General partners will also rely on their internal contacts and possibly the contacts of their limited partners; though in general, as per the structure of the limited partnership (or LLC), the LPs provide capital only.

Once sourcing has produced a viable investment lead, extensive research is done on the prospective company and its market. The business plan and any market analysis is examined during this period of due diligence. In addition, site visits and interviews with management may eventually lead to an investment. A term sheet is created to outline the specifics of the deal. The term sheet is often as complicated as the limited partner agreements with details such as anti-dilution clauses spelled out in the term sheet.
The entrepreneur’s firm is now one of the VC’s "portfolio companies." The venture capital fund is now an equity participant in the start-up firm. The deal structure will typically include one or more of the following—stock, warrants, convertible securities and options. The general partners will then use the committed capital of the fund to provide financing. In addition, one representative from the venture capital firm (or more) will sit on the board of the portfolio company. The primary job of this board member is to provide strategic advice and operational improvements to the management team and to assure that the general partners’ interests are always addressed.

This brings the fund in to the third stage--helping portfolio companies expand and monitor portfolio companies’ growth. If interests are properly aligned, the portfolio company and the VC firm will unite with the common goal of increasing the value of the portfolio company. The relationship between the VC and the start-up is finite from the beginning, so an ancillary goal of the venture capitalist is the all-important exit.

Given the general opaqueness of private equity, information asymmetry is a central concern—to limited partners, general partners and entrepreneurs. Chapter 2 of this thesis explores one aspect of this asymmetry, focusing on private information contained by inexperienced limited partners that wish to signal outside high-ability general partners.

Most research, however, centers on the information asymmetry held by the entrepreneurs. Agency and monitoring costs which arise from investing in a portfolio of entrepreneurs are
significant. It is entirely rational for a failing entrepreneur to be reluctant to reveal this information to its venture capitalist for fear of actions such as management replacement or write-offs. Gompers (1995) examines the implications of these agency costs and explores staged financing, which Gompers shows is an effective response to the private information held by the entrepreneurs. Staged financing allows venture capitalists to keep entrepreneur “burn rates” (the velocity of invested cash expenditures) at reasonable levels and the incentives of the entrepreneur aligned with that of the shareholder (the VC). If a venture capitalist fund believes that there is little hope of a successful exit, it can withhold all further stages of funding, allowing the entrepreneur to experience the effects of Social Darwinism. This minimizes the damage to the fund’s returns and allows the fund to divert capital to other assets that are performing well.

The venture capitalist must properly tend to the growth of the start-up firms, giving them enough capital to continuously grow but not too much capital to create poor incentives. One of the best ways of preventing the entrepreneur from frivolously spend the financing provided by the VC is to stage the financing. Staged financing, or dispersing financing to entrepreneurs over intervals of time (rather than all at once), can address many agency problems. Gompers (1995) shows a positive relationship between the duration of staged investment rounds and the extent to which a firm is monitored by the venture capitalist. With staged financing, informational asymmetry is mitigated between venture capitalists and the portfolio firms. Gompers' (1995) research is one of many research articles which indicate that the structure of investment in the portfolio company is designed not only to
provide financing to a cash-starved business, but to mitigate agency costs between the VC and the start-up firm.

Additional evidence that shows how the structure of the term sheet reduces information asymmetry comes from Sahlman (1989). Sahlman interviewed multiple venture capitalists in the mid-1980s and provided an excellent look into the venture capitalist fund’s relationship with its portfolio companies. It revealed that an intense amount of direct contact occurs between the VC and its portfolio companies. Each venture capital fund averaged nine start-ups in its portfolio. Representatives from the venture capitalist sat on more than half of the portfolio company boards. The venture capitalists in the survey replaced an average of three CEOs during their tenure in private equity. They cited poor senior management as the primary cause for write-offs. In total, this suggests that the relationship between the venture capitalist and the portfolio company during the monitoring stage is an active one.

The fourth and final stage in the life of a venture fund is its closing. By the expiration date of the fund, the VC firm will hopefully have liquidated its position in all of its portfolio companies (though some follow-on fund can take up the mantle of investment if the venture capitalist deems the start-up too young to exit and too valuable to write off). Exits come in three basic varieties: the complete write-off of the portfolio company, the acquisition of the portfolio company by a buyer, or an Initial Public Offering (IPO). For the standard-bearer on the venture capital cycle, see Gompers and Lerner (2001).
1.1.4 The Venture Capital Investment

Once the fund has been established and capital has been raised, the venture capitalist will begin sourcing deals. The venture capitalist is concerned with the life cycle of the start-up from its birth (the entrepreneur’s idea) to its departure from the realm of venture capital (by means of one of three aforementioned exits). Many venture capitalists will focus primarily on one stage of development, committing capital only at that particular stage while others will source deals across the life cycle.

For example, Academy Funds is a VC firm that invests in information technology and telecommunications. It restricts its initial investments to firms that are classified as early venture (defined below). Once capital is committed, Academy will monitor the investment, adding capital in stages as the company grows. The exit may occur at a later stage of the company’s development (in this case, Academy Funds has participated in at least one IPO at the time of this Chapter’s writing), but the initial sourcing occurs only during early stages.

On the other hand, Kinetic Ventures LLC., also a firm which invests primarily in information technology and telecommunications, will invest across multiple stages. They have sourced deals in what is known as early venture, mid venture and late venture stages with multiple IPO exits to their credit.
Figure 2 presents the typical life cycle of a start-up. The text above the progression of revenue (often called the “j-curve”) shows each stage in the growth of the firm as it relates to profitability levels. The text underneath the j-curve shows typical entry points for outside funding.  

Prior to any external funding, the entrepreneur must rely on his own capital and any friends or family that may be committed to the idea. Once the idea begins to coalesce around a prototype, the entrepreneur may seek external funding. This is the time for seed capital. During the seed capital stage, the company is still typically just the entrepreneur. A business plan may or may not be present, some sort of prototype may be built but it is only

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3 There are multiple ways stages are defined in the literature (e.g., some refer only to early and later stage, some refer to early, mid and later stage). This chapter will follow the descriptions of the Capital IQ data set used in the construction of the data set in Chapter 3.
marginally past the “concept.” Seed capital can be venture capital (called seed-stage VCs), though this stage of development is typically more associated with angel investors⁴.

A completed and well-developed business plan is usually one line of demarcation between the seed capital phase and the early venture phase. At this point, the entrepreneur probably has some sort of management team, though it might not be filled with experienced professionals. A prototype almost certainly exists at this point and production or provision of services may be starting. This is the realm of early stage venture capitalists. The use of venture capital to professionalize the firm has been well-documented. For example, Hellmann and Manju (2000) show that once venture capital begins to commit capital, the probability of an outside CEO increases dramatically. In addition, they show that the entrepreneurs themselves will leave the firm at a greater rate once venture capital money is committed. Florin (2005) actually shows that the influx of venture capital is negatively correlated with expected returns for the entrepreneur.

By what is known as the mid venture stage, the firm’s infrastructure is in place and it may have had multiple rounds of early stage financing at this point. The product (or service) is generating revenue and forecasts of future revenue can be estimated with slightly greater precision. At this point the firm is still burning cash faster than it is generating capital.

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⁴ Angel investors are typically wealthy individuals, families or foundations who invest in start-ups; they differ from venture capital in that venture capitalists are professional money managers of other institutions capital (the limited partners)
The late venture stage is the last “traditional” entry point of venture capital (though VCs do enter much later, see below). Here the firm will have multiple strategic relationships with suppliers and customers. Revenue is strong enough to bring the firm close to a break-even level of sales and projections are certainly positive.

The next phase of development is the expansion stage, sometimes called the emerging growth phase (this is not to be confused with “growth capital” which is typically any extra infusion of capital, sourced from venture capitalists or other private equity). The expansion stage occurs as the company begins to expand its market share. At this point the product or service may be entering its second (or even third) generation of development. The ultimate goal here is typically an IPO, though the company may be a target of a strategic buyer at this point.

As the company grows, it may require additional capital. To prevent the dilution of equity holdings, mezzanine and/or bridge financing may be employed. Mezzanine financing, which can be financed by a venture capitalist, is typically a blend of debt (often convertible) and equity. Bridge financing is usually shorter-term debt used to cover gaps in capital as the firm nears IPO.

1.2 The History and Evolution of Venture Capital in the United States

The history of venture capital is a history of modern entrepreneurialism. This section reviews the development of the asset class from its proto post World War II beginnings, to its expansion from new supplies of capital to two major declines in the early 21st century.
The first decline followed the meteoric rise driven by the information technology (IT) boom of the 1990s. This affected both VC returns and VC funding. A second major decline in VC funding followed the credit crisis of 2008, though effect on VC returns is yet unclear. As of 2011, the future of venture capital funding is in question, as the current Administration and Congress consider major structural changes to commercial banking proprietary investing which will preclude commercial banks from investing in private equity.

1.2.1 The Early Years

The first true venture capital firm, American Research and Development (ARD), was developed by Massachusetts Institute of Technology President Karl Compton and U.S. Army General Georges Doriot after World War II. A strategic response to the Cold War, this arrangement had nationalist underpinnings, as the research was designed to help support U.S. development against Soviet technology. Doriot believed that much of the technology developed in World War II had yet to be properly exploited by the market. Though it did not reach its target capitalization (only obtaining 60% of target), it helped bring several successful firms to the marketplace, including its most profitable investment, Digital Enterprise Corporation. Similar to Julian Robertson and his “Tiger Cubs,” ARD employees went on to establish other prominent venture capital firms such as Greylock Partners and Morgan Holland Ventures.
ARD was a publicly traded closed-end fund; far different from the current expression of the venture capital fund. The closed-end fund was not the only incarnation of venture capital. The competing business structure was the Small Business Investment Company (SBIC). The SBICs were federally chartered pools of capital for risky ventures. They initially held a distinct advantage over closed-end funds in that investors received matching funds from the Federal government. During the 1960s and 1970s, venture capital was dominated by both SBICs and closed-end funds. However, the moral hazard created from these government-guaranteed entities led to risk-taking which eventually collapsed the SBIC industry. The Limited Partnership soon became the business model of choice for the venture capital industry.

1.2.2 The Rise of the Limited Partnership

The first limited partnership, Draper, Gaither and Anderson, was formed in 1958. It was originally organized to have a predetermined finite lifetime. By separating the investors from those who ran the day to day operations, the general partners, the Limited Partnership created the limited liability shield. Its structure allowed investors to be protected from liabilities beyond their invested capital. The limited partner is relegated to the role of mostly passive investor. This creates a situation of information asymmetry in which information about the quality of the Limited Partner is kept from the General Partner and vice versa. In later years, the limited liability company (LLC) became an attractive alternative to the limited partnership, as it provided limited liability to the general partners as well.
In addition to the liability shield, the limited partnership is not taxed as a corporation. This is particularly advantageous to tax-exempt institutions, though one of the largest institutional investors, pension funds, were initially excluded from investing in venture capital explicitly by the Employee Retirement Income Security Act of 1974.

The compensation structure of the limited partnership is typically a blend of a management fee and a performance fee (carried interest). The management fee is applied annually to capital committed (not actual capital drawn down or invested). Performance fees are based entirely on profits from successful exits. Throughout the 60s and 70s, the management fee hovered around 1-2% and carried interest was typically 20%. (NVCA, 2009)

Much of the industry during this time found its roots in Menlo Park, CA. Venture capital giants Kleiner, Perkins, Caulfield & Byers and Sequoia Capital formed there to take advantage of the technology firms located there. Fed by research Stanford University and industry from the Stanford Industrial Park, this area of California south of San Francisco and north of San Jose would eventually become known as Silicon Valley. In addition, South San Francisco, home to giants such as Genentech and Amgen, was a biotechnology capital. These firms were fueled by venture investments and help attract new venture capitalists to the area. The region would be the heart of technology-driven venture capital and the source of the I.T. boom of the 1990s.
In 1974, venture capital as an asset class suffered two setbacks. The demand for venture
capital, discussed further in Chapter 3, has always been fueled by a strong public market
(which implies a robust IPO market). In 1974 the stock market declined sharply and
investors shied away from committing capital to risky private ventures. In addition, the
Employee Retirement Income Security Act of 1974 separated private equity from the
universe of ‘prudent’ securities in which a pension fund manager may invest. However, in
1979, the Department of Labor clarified the “prudent man rule” to allow pension fund
managers to invest in high-risk assets such as private equity.

1.2.3 The Prudent Man Invests

Prior to the ERISA clarification, private equity (which includes venture capital as well as
buyout firms and mezzanine funds) was viewed as too risky to be sought after by those
acting prudently. The Department of Labor recognized that diversification across asset
classes can better protect capital in down markets. Venture capital’s historical low
correlation with domestic equity appeared to make it a perfect candidate for diversification.
This clarification, combined with the pass-through taxation (taxes are not applied to the
business’s income) of the limited partnership made venture capital particularly attractive to
the tax-exempt pension funds (as well as other institutional investors, such as
endowments). Though it took several years, vast amounts of pension fund money began to
move into the venture industry, flowing first from corporate pension funds and then from
public pension funds. (Pensions and Investments)
Even the bursting of the I.T. Bubble during 2000 did not stem the influence of pension funds in the VC industry. In 2001 pension funds represented more than 50% of capital committed (NVCA, 2002). Though formidable with respect to the VC industry, capital committed still only represents a tiny fraction of the overall pension fund universe. In 2001, the universe of pension funds had assets valued at nearly $3.6 trillion in defined benefit plans but allocated only 0.8% of total assets to venture capital (Pensions and Investments).

Endowments also represent an important contingent of venture capital investors. Following practices such as the Swenson Model of Yale, private University endowments continue to increase their allocations to alternative assets such as hedge funds and private equity (Swenson 2001).

For example, by 2006, the Princeton endowment allocated 19% of its policy portfolio (its long range allocations) to private equity. Compare this to a policy allocation of 7% to fixed income (and 0% to cash). Other large private institutions had similar asset allocations (e.g. Yale 17%, Harvard 13%, and MIT 20%) in 2006. In 2008, the average allocation to private equity for all universities and colleges with over $1 billion endowments was 13.6% (with roughly 26% of that devoted to the asset subclass venture capital). Endowments with asset pools of between $500 million and $1 billion dedicated 10.5% of their assets under management to the private equity asset class (with 27% of that contributed to venture capital). Though these percentages were lower for smaller endowments, it is clear that
private equity and by extension venture capital had become entrenched parts of the endowments and pension funds. (www.nacubo.org)

1.2.4 From Information Technology Boom to Credit Crisis Bust

Of the three exits from venture capital investments, the most potentially profitable is the IPO. The probability that portfolio companies will become publicly traded through an IPO is dependent not just on the quality and demand of the product or service it produces and the ability of its management team but on the conditions present in the broader IPO market. It will be shown below that the appetite for venture capital backed IPOs moved in strong correlation with the general IPO market. The IPO market itself was a function of multiple macroeconomic and market conditions, with two in particular of note—the technology boom of the 1990s and the credit crisis of 2007 to 2009.

After the rise of the institutional investor as the major limited partners for venture capitalists, the technology boom of the late 1990s begins to build momentum. Even with the Asian currency crisis of 1997, the technology boom in the United States drove the venture capital industry to new levels of commitment and new records for the size and the number of IPOs. Gompers and Lerner (1998) and Gompers and Lerner (2001) document well the rise in fund size and IPOs during this time period. Venture capital also begins to shift committed capital into the growing field of information technology. As Table 1 shows, during the late 1990s, IT services, networking and software all grew as percentages of committed capital.
Table 1: Industries as a Percentage of Venture Capital Commitments

<table>
<thead>
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</thead>
<tbody>
<tr>
<td>Biotechnology</td>
<td>10%</td>
<td>11%</td>
<td>10%</td>
<td>8%</td>
<td>4%</td>
<td>4%</td>
<td>9%</td>
<td>15%</td>
<td>19%</td>
<td>17%</td>
<td>17%</td>
<td>17%</td>
<td>16%</td>
<td>20%</td>
<td></td>
</tr>
<tr>
<td>Business Products and Services</td>
<td>2%</td>
<td>3%</td>
<td>3%</td>
<td>5%</td>
<td>4%</td>
<td>3%</td>
<td>2%</td>
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<td>2%</td>
<td>1%</td>
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<tr>
<td>Computers and Peripherals</td>
<td>4%</td>
<td>4%</td>
<td>3%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
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<td>2%</td>
<td>2%</td>
<td>2%</td>
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<td>2%</td>
</tr>
<tr>
<td>Consumer Products and Services</td>
<td>6%</td>
<td>5%</td>
<td>5%</td>
<td>3%</td>
<td>2%</td>
<td>1%</td>
<td>1%</td>
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<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>Electronics/Instrumentation</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
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<td>2%</td>
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<tr>
<td>Financial Services</td>
<td>2%</td>
<td>3%</td>
<td>3%</td>
<td>4%</td>
<td>4%</td>
<td>4%</td>
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</tr>
<tr>
<td>Healthcare Services</td>
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<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>Industrial/Energy</td>
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<td>5%</td>
<td>5%</td>
<td>7%</td>
<td>3%</td>
<td>2%</td>
<td>3%</td>
<td>3%</td>
<td>4%</td>
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<td>7%</td>
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</tr>
<tr>
<td>Media Entertainment</td>
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<td>9%</td>
<td>13%</td>
<td>10%</td>
<td>6%</td>
<td>3%</td>
<td>4%</td>
<td>4%</td>
<td>5%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
</tr>
<tr>
<td>Medical Devices and Equipment</td>
<td>8%</td>
<td>6%</td>
<td>7%</td>
<td>5%</td>
<td>3%</td>
<td>2%</td>
<td>5%</td>
<td>9%</td>
<td>8%</td>
<td>8%</td>
<td>10%</td>
<td>11%</td>
<td>12%</td>
<td>12%</td>
<td>14%</td>
</tr>
<tr>
<td>Networking and Equipment</td>
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<td>6%</td>
<td>7%</td>
<td>7%</td>
<td>8%</td>
<td>11%</td>
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<td>7%</td>
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<td>4%</td>
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<tr>
<td>Other</td>
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<td>0%</td>
<td>0%</td>
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<td>0%</td>
</tr>
<tr>
<td>Retailing/Distribution</td>
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<td>2%</td>
<td>2%</td>
<td>5%</td>
<td>5%</td>
<td>3%</td>
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<td>1%</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>Semiconductors</td>
<td>3%</td>
<td>3%</td>
<td>4%</td>
<td>3%</td>
<td>2%</td>
<td>3%</td>
<td>6%</td>
<td>7%</td>
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<td>8%</td>
<td>7%</td>
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<td>4%</td>
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<tr>
<td>Software</td>
<td>15%</td>
<td>20%</td>
<td>23%</td>
<td>21%</td>
<td>20%</td>
<td>24%</td>
<td>26%</td>
<td>24%</td>
<td>23%</td>
<td>24%</td>
<td>21%</td>
<td>18%</td>
<td>18%</td>
<td>16%</td>
<td></td>
</tr>
<tr>
<td>Telecommunications</td>
<td>12%</td>
<td>11%</td>
<td>10%</td>
<td>13%</td>
<td>15%</td>
<td>16%</td>
<td>13%</td>
<td>10%</td>
<td>9%</td>
<td>8%</td>
<td>10%</td>
<td>10%</td>
<td>7%</td>
<td>6%</td>
<td>3%</td>
</tr>
</tbody>
</table>

Source: Venture Economics

Figures 3 and 4 present the increasing and declining investment trends before and after the technology boom. Figure 3 shows increasing trends in biotechnology and medical devices and equipment, no doubt a function of an aging population. Similarly, the technology driven fields of networking, telecommunication and media equipment peaked in the late 1990s but have fallen below pre-boom percentages of the overall venture capital universe. Figure 4 shows this trend.
Figure 3:
Venture Capital Investment Trends: Increasing
This figure shows the industries, which as a percentage of overall capital commitments have been trending up since 1995.

Source: Venture Economics

Figure 4:
Venture Capital Investment Trends: Decreasing
This figure shows the industries, which as a percentage of overall capital commitments have been trending down since 1995.

Source: Venture Economics
Venture capital deals to entrepreneurs grew in the 1990s and peaked in 2000 with over $100 billion dollars committed in that year. The NASDAQ composite reached its peak on March 10, 2000, which marks the beginning of the end of I.T. bubble. As described in the previous section, the demand for venture money within information technology was massive and I.T. companies filled the portfolios of generalist and specialist venture capital funds. The rapid collapse of the public I.T. market signaled the end of a robust IPO market. This, in turn, devastated the venture capital returns for vintage years 1999 and 2000. Table 2 shows the number of deals, the total capital commitments and the average deal size during the pre-boom venture capital universe.

<table>
<thead>
<tr>
<th>Year</th>
<th>Average Deal Size (Millions)</th>
<th>Total VC Investment (Millions)</th>
<th>Total VC Deals per Calendar Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>$4.35</td>
<td>$7,996</td>
<td>1,839</td>
</tr>
<tr>
<td>1996</td>
<td>$4.38</td>
<td>$11,265</td>
<td>2,571</td>
</tr>
<tr>
<td>1997</td>
<td>$4.71</td>
<td>$14,871</td>
<td>3,155</td>
</tr>
<tr>
<td>1998</td>
<td>$5.78</td>
<td>$21,079</td>
<td>3,647</td>
</tr>
<tr>
<td>1999</td>
<td>$9.37</td>
<td>$51,476</td>
<td>5,496</td>
</tr>
<tr>
<td>2000</td>
<td>$12.75</td>
<td>$100,663</td>
<td>7,894</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>$8.43</strong></td>
<td><strong>$34,558</strong></td>
<td><strong>4,100</strong></td>
</tr>
</tbody>
</table>

Source: Venture Xpert

Total yearly venture capital investments have since fallen from these levels to an average of about $26 billion per year during the post-Dotcom/pre-Credit Crisis world. The average deal size during this time period fell from $8.43 million to $7.30 million. Table 3 contains these results. Though limited partner committed capital only fell 2.7% compared to 2008 levels, capital committed to deals to entrepreneurs fell 46% in the first three quarters of 2009 compared to the first three quarters of 2008.
1.3 Venture Capital Data and Performance

Measuring the performance of venture capital presents similar challenges to the difficulties in measuring hedge fund performance. Funds are not publicly traded and are therefore not required to report their performance to the Securities and Exchange Commission. As such, any performance data provided to private databases will be done on a voluntary basis. There is great potential for bias in the data and multiple studies have addressed this.

1.3.1 Data Sources

One of the most difficult areas to overcome in developing coherent discussions of venture capital returns is the lack of readily available data. Incomplete or highly biased data tend to be the only data available. While there are multiple data sources available to researchers, only a few are repeatedly used in academia. Most researchers will use the venture capital

<table>
<thead>
<tr>
<th>Year</th>
<th>Average Deal Size (Millions)</th>
<th>Total VC Investment (Millions)</th>
<th>Total VC Deals per Calendar Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001</td>
<td>$8.63</td>
<td>$38,692</td>
<td>4,486</td>
</tr>
<tr>
<td>2002</td>
<td>$6.76</td>
<td>$21,046</td>
<td>3,114</td>
</tr>
<tr>
<td>2003</td>
<td>$6.47</td>
<td>$19,165</td>
<td>2,960</td>
</tr>
<tr>
<td>2004</td>
<td>$7.05</td>
<td>$21,989</td>
<td>3,117</td>
</tr>
<tr>
<td>2005</td>
<td>$7.19</td>
<td>$22,945</td>
<td>3,193</td>
</tr>
<tr>
<td>2006</td>
<td>$7.06</td>
<td>$26,439</td>
<td>3,743</td>
</tr>
<tr>
<td>2007</td>
<td>$7.59</td>
<td>$30,539</td>
<td>4,022</td>
</tr>
<tr>
<td>2008</td>
<td>$7.02</td>
<td>$27,959</td>
<td>3,980</td>
</tr>
<tr>
<td>2009 Q1-Q3</td>
<td>$6.41</td>
<td>$12,247</td>
<td>1,910</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>$7.30</strong></td>
<td><strong>$23,860</strong></td>
<td><strong>3,270</strong></td>
</tr>
</tbody>
</table>

Source: Venture Xpert
data provided by Venture Xpert and Thomson Reuters, known as Venture Economics, or they will use Venture One, a subsidiary of Dow Jones Financial Information Services. Cambridge Associates data, which has collected fund reports since the early 1980s, provides its members (private equity firms and institutional investors) access to the reports generated by the proprietary database it owns. Though the venture capital performance index, separated by vintage year (see Table 5) is available to researchers, the underlying granular data is not accessible. Much of the data provided in this chapter is also provided by the Venture Economics database. I use the information on company level data from Venture One and industry data from all three sources.

A final data source is worth mentioning—Capital IQ, also a division of Standard & Poor’s. Capital IQ has an extensive repository of private equity company level data, with self-reported characteristics such as industry of focus and stage of investment reported. This data set is designed primarily for industry, as a quick use of the screening functions will reveal. The advantage of using a data set such as this is that it makes no attempt to collect “performance” data, only company statistics and actual business transaction (e.g., the transaction value of a firm’s IPO). These data were not designed for academic use, though Chapter 3 builds a data set out of the Capital IQ database which relies on self-reported characteristics. Though there is always the potential for reporting bias, it should be less so here, since Capital IQ does not have a mechanism to assess the performance of individual funds in any way.
Benchmarking venture capital performance may be even more difficult than it is in the hedge fund universe. While they are both private investment vehicles, many hedge funds at least hold publicly traded securities. On the other hand, venture capital firms are private entities and invest only in private equity which is not marked to market.

1.3.2 Venture Capital Performance Benchmarks

Reported venture capital returns from Venture Economics combines both valuations from unrealized investments and realized investments. The inclusion of unrealized investments can skew results, as accounting write-ups that have not realized cash inflows are misleading. In addition, GAAP does not apply to these write-ups. Thus, Blaydon and Horvath (2002) decompose syndicated ventures and show that for the same investments, different private equity funds assess different values. The rationale behind such choices is fairly straightforward. First time firms may be more aggressive in their valuation to improve confidence with their limited partners. First time funds are particularly susceptible to this aggressive accounting. Established funds will be more conservative in their accounting approach. Thus assessed values of unrealized investments make for imprecise return data sets.

One direct attempt at eliminating the bias present in other datasets comes from the construction of a database that claims to be essentially unbiased, developed by Sand Hill Econometrics. Driven by the work of Susan Woodward, this database is now the Dow Jones venture capital Index. The index, which has been folded into the Dow Jones
VentureSource database is value-weighted, and tracks 18,000 companies (most of which have already exited via IPO or acquisition). To minimize selection bias, the index uses a two-pronged approach. It builds the model on company, rather than fund, level data (as venture capital companies will publicly declare their intent to raise a fund), directly contacting companies where fund data are missing. For companies that do not provide the necessary information for their funds (since reporting is voluntary by definition of the private firm), Sandhill Econometrics imputes missing data from equations that it believes have had bias removed. It uses the results of tracking down previously missing data as a guide to imputing the remaining missing data. Though their methodology is fairly well guarded, they do state in a white paper dedicated to their approach, that they draw inspiration from Heckman’s two-stage estimator.

1.4 Venture Capital Returns

Even with the difficulties present in benchmarking venture capital, many good studies on performance exist. Kaplan and Schoar (2005) found that average private equity fund returns were roughly equal to the returns of the S&P 500 over the same period (1980-1997). When each VC firm was equally weighted, returns for the funds were slightly less than those of the S&P 500; while when each firm was weighted based on committed capital the average returns were slightly higher than the S&P 500. In both of these instances, fund returns were net of any fees. However, when they broke their sample into two groups, venture capital and buyouts, they found that when weighted by committed capital the venture firms outperformed the S&P 500 while the buyout firms did not.
Kaplan and Schoar do acknowledge that the average returns are potentially biased for two possible reasons—first, they did not know the beta of each firm, so they assumed that each firm had a beta of 1. This could have caused them to overstate or understate the true risk-adjusted returns if the true beta is higher or lower than 1, respectively. It may be worth pointing out that Kaplan and Schoar believe that the true betas of these private equity firms may be greater than 1, because they claim that these funds tend to invest in highly leveraged companies. Other researchers disagree. Moskowitz and Vissing-Jorgenson (2002) find that a portfolio of all private equity has a mean and standard deviation of return close to those of the value weighted index of traded stocks.

Kaplan and Schoar (2005) also found that returns persist strongly across funds raised by the same general partners. In other words, an increase in past performance is associated with an increase in performance of subsequent funds. They used different methods of analysis to try and rule out selection bias or bias from differences in risk in the persistence, and found these biases not to be present. Kaplan and Schoar present evidence that funds created during hot IPO markets are less likely to raise follow-on funds. They suggest this implies a boom and bust cycle in the private equity industry—above-market returns lead to entry into the market, which in turn leads to below market returns for the private equity industry.

Capital flows into private equity funds are positively related to past fund performance, but with negative second order conditions. In other words, while successful mutual funds grow at a growing rate, the better private equity funds grow but at a decreasing rate. Kaplan and Schoar suggest this concave relationship in private equity funds is a result of the resistance
to grow for the sake of growth. Superior general partners might choose to remain small and grow slower in order to avoid diseconomies of scale\(^5\).

Kaplan and Schoar express the opinion that the best explanation for the differences in the relationship between capital inflows and past performance between mutual funds and private equity funds, and also for the persistence results, is heterogeneity in GP skill. However, they point out that across all private equity funds, GP compensation remained fairly constant, which is puzzling because if GP skill is heterogeneous, reason would lead us to believe that better performing GPs would seek higher compensation. This does not account for improved probability of follow-on fund raising which follows successful funds.

Cochrane (2005) addresses selection bias with a different approach. He looks at projects, not funds, when calculated results which include expected return, standard deviation, alpha, and the beta of VC investments. He uses venture capital data from the VentureOne database from 1987 to June 2000. To supplement the missing exit data, he matches the VentureOne data with exit results (mergers and IPOs) from the SDC Platinum Corporate New Issues and Mergers and Acquisitions (M&A) databases and from MarketGuide.

He uses only observable cash flows, which including financing rounds and exits (IPOs and acquisitions). Also, since the data are project level, he does not net out performance and management fees. Before correcting for selection bias, the average arithmetic mean for projects that exit by IPO or acquisition is 698% with a standard deviation of 3,282%.

\(^5\) In other words, there are only so many good ideas out there at any given time. With mutual funds, the management fees incentivize this growth, though the same diseconomies of scale exist.
Venture capital returns are skewed (a few IPOs with thousands of percent returns, many 100% returns and many write-offs), so he calculates log returns. The log returns still have a large 108% arithmetic mean and 135% standard deviation.

The primary contribution of Cochrane (2005) is to correct for selection bias (which he defines as the lack of independence between the probability of observing a return and the project’s value). To this end, he uses a maximum-likelihood estimator. The selection bias correction dramatically lowers these estimates. Mean arithmetic returns drop from 698% to 59%. The estimated average log return is 15% per year, not 108%. He shows that these returns are still high, but the behavior of the distribution is closer to the returns generated by the smallest decile of the NASDAQ.

1.4.1 Fund IRR and Benchmark Performance

A typical manner of calculating venture capital performance is through the internal rate of return, generally calculated for funds by vintage year. When developing a benchmark, it is useful to note that the number of VC firms reporting is far less than funds per year, since most VC firms will have multiple funds across vintage years. Given both the skewed nature of venture capital returns and the relative small number of funds reporting for each vintage year, both the mean and the median were included in Tables 4 and 5. The overall coverage of these databases is limited. For example, Table 4 shows the IRRs for funds in the Venture Economics data base. In 2007, 22 funds reported to this database out of a total of 233 funds with vintage year 2007, or a little less than 10% coverage. Similarly, Table 5
shows the funds reporting to Cambridge Associates. At 50 in 2007, Cambridge covers about 21% of the VC universe (by number of funds).

### Table 4: Venture Economics Fund Performance

This table shows the internal rates of return (IRR) generated by the cash flows of funds reporting to Venture Economics. The IRRs for the last several vintage years are practically meaningless, as few of the portfolio companies have exited and the rest are typically valued at cost. Source: Venture Economics, Thomson Reuters

<table>
<thead>
<tr>
<th>Vintage Year</th>
<th>Number of Funds Reporting</th>
<th>Mean Unweighted IRR (%)</th>
<th>Cap. Weighted Mean IRR (%)</th>
<th>Mean Pooled IRR (%)</th>
<th>Median IRR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1981</td>
<td>22</td>
<td>8.0</td>
<td>10.3</td>
<td>10.9</td>
<td>9.9</td>
</tr>
<tr>
<td>1982</td>
<td>28</td>
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<tr>
<td>1983</td>
<td>59</td>
<td>5.2</td>
<td>6.6</td>
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</tr>
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<td>1984</td>
<td>64</td>
<td>5.0</td>
<td>6.1</td>
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<tr>
<td>1985</td>
<td>46</td>
<td>8.2</td>
<td>9.2</td>
<td>10.0</td>
<td>8.7</td>
</tr>
<tr>
<td>1986</td>
<td>43</td>
<td>7.0</td>
<td>10.1</td>
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<td>63</td>
<td>7.6</td>
<td>13.5</td>
<td>14.6</td>
<td>7.8</td>
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<td>1988</td>
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<td>12.3</td>
<td>19.8</td>
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<td>9.5</td>
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<td>1989</td>
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<td>16.3</td>
<td>17.8</td>
<td>10.9</td>
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<td>22</td>
<td>17.5</td>
<td>24.4</td>
<td>28.1</td>
<td>14.0</td>
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<tr>
<td>1991</td>
<td>18</td>
<td>18.7</td>
<td>28.9</td>
<td>28.4</td>
<td>17.8</td>
</tr>
<tr>
<td>1992</td>
<td>27</td>
<td>26.1</td>
<td>29.4</td>
<td>35.5</td>
<td>13.7</td>
</tr>
<tr>
<td>1993</td>
<td>41</td>
<td>21.5</td>
<td>28.6</td>
<td>37.4</td>
<td>12.5</td>
</tr>
<tr>
<td>1994</td>
<td>39</td>
<td>25.3</td>
<td>32.8</td>
<td>39.2</td>
<td>15.6</td>
</tr>
<tr>
<td>1995</td>
<td>48</td>
<td>45.5</td>
<td>57.1</td>
<td>59.8</td>
<td>20.3</td>
</tr>
<tr>
<td>1996</td>
<td>36</td>
<td>74.0</td>
<td>59.2</td>
<td>83.0</td>
<td>33.2</td>
</tr>
<tr>
<td>1997</td>
<td>62</td>
<td>49.2</td>
<td>46.0</td>
<td>49.3</td>
<td>20.0</td>
</tr>
<tr>
<td>1998</td>
<td>76</td>
<td>26.0</td>
<td>23.4</td>
<td>17.6</td>
<td>1.2</td>
</tr>
<tr>
<td>1999</td>
<td>110</td>
<td>-5.1</td>
<td>-7.0</td>
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<td>-6.0</td>
</tr>
<tr>
<td>2000</td>
<td>126</td>
<td>-2.2</td>
<td>-0.4</td>
<td>0.5</td>
<td>-3.1</td>
</tr>
<tr>
<td>2001</td>
<td>57</td>
<td>0.7</td>
<td>0.9</td>
<td>1.9</td>
<td>-0.6</td>
</tr>
<tr>
<td>2002</td>
<td>20</td>
<td>0.4</td>
<td>0.3</td>
<td>1.7</td>
<td>-1.1</td>
</tr>
<tr>
<td>2003</td>
<td>17</td>
<td>3.4</td>
<td>3.8</td>
<td>3.7</td>
<td>3.0</td>
</tr>
<tr>
<td>2004</td>
<td>23</td>
<td>-1.5</td>
<td>-0.3</td>
<td>0.4</td>
<td>-2.4</td>
</tr>
<tr>
<td>2005</td>
<td>20</td>
<td>-0.1</td>
<td>0.3</td>
<td>3.1</td>
<td>-1.1</td>
</tr>
<tr>
<td>2006</td>
<td>33</td>
<td>-8.5</td>
<td>-5.9</td>
<td>-4.9</td>
<td>-5.9</td>
</tr>
<tr>
<td>2007</td>
<td>22</td>
<td>-10.5</td>
<td>-12.0</td>
<td>-5.8</td>
<td>-15.8</td>
</tr>
<tr>
<td>2008</td>
<td>9</td>
<td>-43.8</td>
<td>-42.2</td>
<td>-35.7</td>
<td>-36.5</td>
</tr>
</tbody>
</table>
Contrast these returns with the publicly available returns provided by Cambridge Associates⁶, Table 5. Note the difference in IRRs and the number of funds reporting.

Table 5: Cambridge Associates Fund Performance
This table shows the internal rates of return (IRR) generated by the cash inflows and cash outflows of all funds reported in the Cambridge Associates VC Index. The IRRs for the last several vintage years are unreliable, as few of the portfolio companies have exited and the rest are typically valued at cost. Source: Cambridge Associates

<table>
<thead>
<tr>
<th>Vintage Year</th>
<th>Number of Funds Reporting</th>
<th>Mean Unweighted IRR (%)</th>
<th>Cap. Weighted Mean IRR (%)</th>
<th>Mean Pooled IRR (%)</th>
<th>Median IRR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1981</td>
<td>9</td>
<td>9.03</td>
<td>9.01</td>
<td>8.47</td>
<td>7.87</td>
</tr>
<tr>
<td>1982</td>
<td>11</td>
<td>7.37</td>
<td>7.21</td>
<td>7.38</td>
<td>7.92</td>
</tr>
<tr>
<td>1983</td>
<td>28</td>
<td>10.09</td>
<td>9.55</td>
<td>10.23</td>
<td>8.72</td>
</tr>
<tr>
<td>1984</td>
<td>32</td>
<td>8.1</td>
<td>7.74</td>
<td>8.62</td>
<td>6.27</td>
</tr>
<tr>
<td>1985</td>
<td>25</td>
<td>12.8</td>
<td>11.58</td>
<td>12.9</td>
<td>12.66</td>
</tr>
<tr>
<td>1986</td>
<td>30</td>
<td>9.12</td>
<td>8.82</td>
<td>14.52</td>
<td>9.43</td>
</tr>
<tr>
<td>1987</td>
<td>34</td>
<td>15.83</td>
<td>14.53</td>
<td>18.27</td>
<td>15.65</td>
</tr>
<tr>
<td>1988</td>
<td>26</td>
<td>14.73</td>
<td>14.32</td>
<td>18.9</td>
<td>11.87</td>
</tr>
<tr>
<td>1989</td>
<td>37</td>
<td>18.88</td>
<td>17.05</td>
<td>19.16</td>
<td>13.32</td>
</tr>
<tr>
<td>1990</td>
<td>16</td>
<td>26.54</td>
<td>24.25</td>
<td>33.96</td>
<td>21.86</td>
</tr>
<tr>
<td>1991</td>
<td>17</td>
<td>24.81</td>
<td>23.01</td>
<td>26.77</td>
<td>18.56</td>
</tr>
<tr>
<td>1992</td>
<td>23</td>
<td>37.33</td>
<td>28.69</td>
<td>32.79</td>
<td>20.99</td>
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<tr>
<td>1993</td>
<td>37</td>
<td>39.5</td>
<td>29.5</td>
<td>46.65</td>
<td>18.81</td>
</tr>
<tr>
<td>1994</td>
<td>42</td>
<td>45.15</td>
<td>34.55</td>
<td>55.63</td>
<td>26.45</td>
</tr>
<tr>
<td>1995</td>
<td>34</td>
<td>76.62</td>
<td>56.76</td>
<td>87.95</td>
<td>42.92</td>
</tr>
<tr>
<td>1996</td>
<td>40</td>
<td>89.16</td>
<td>61.15</td>
<td>103.28</td>
<td>37.05</td>
</tr>
<tr>
<td>1997</td>
<td>73</td>
<td>72.1</td>
<td>52.77</td>
<td>90.97</td>
<td>8.63</td>
</tr>
<tr>
<td>1998</td>
<td>81</td>
<td>15.21</td>
<td>18.2</td>
<td>12.32</td>
<td>0.38</td>
</tr>
<tr>
<td>1999</td>
<td>112</td>
<td>-1.36</td>
<td>-3.72</td>
<td>-1.06</td>
<td>-4.58</td>
</tr>
<tr>
<td>2000</td>
<td>155</td>
<td>-2.2</td>
<td>-4</td>
<td>-1.04</td>
<td>-3.53</td>
</tr>
<tr>
<td>2001</td>
<td>52</td>
<td>1.54</td>
<td>-1.84</td>
<td>1.16</td>
<td>-0.22</td>
</tr>
<tr>
<td>2002</td>
<td>32</td>
<td>0.42</td>
<td>-0.27</td>
<td>0.14</td>
<td>-0.43</td>
</tr>
<tr>
<td>2003</td>
<td>34</td>
<td>1.88</td>
<td>0.13</td>
<td>4.8</td>
<td>0.92</td>
</tr>
<tr>
<td>2004</td>
<td>64</td>
<td>7.63</td>
<td>1.55</td>
<td>7.98</td>
<td>0.76</td>
</tr>
<tr>
<td>2005</td>
<td>58</td>
<td>1.5</td>
<td>-1.35</td>
<td>3.16</td>
<td>0.75</td>
</tr>
<tr>
<td>2006</td>
<td>67</td>
<td>-0.29</td>
<td>-1.53</td>
<td>2.36</td>
<td>-0.63</td>
</tr>
<tr>
<td>2007</td>
<td>50</td>
<td>4.08</td>
<td>2.32</td>
<td>5.82</td>
<td>2.79</td>
</tr>
<tr>
<td>2008</td>
<td>55</td>
<td>1.92</td>
<td>-1.73</td>
<td>11.19</td>
<td>-3.4</td>
</tr>
</tbody>
</table>

⁶ The fund level, granular data are not available, only the overall returns.
The correlations between the reported data are high: Weighted IRR: 89%, Arithmetic Mean IRR: 92%, Pooled IRR: 90% and Median IRR: 78%\(^7\). This suggests that aside from the biases described by Cochrane (2005), there are no additional systematic biases of one dataset over the other. Figure 5 further confirms this; as the excess returns of the Venture Economics pooled IRRs against the Cambridge Associates pooled IRRs appear random with no pattern. While simple difference of means tests conducted show that the underlying data are significantly different from each other, Figure 5 shows there is no pattern to this difference.

\(^7\) Even the number of funds reporting was highly correlated between the two databases, 72%.
1.4.2 Venture Capital’s Offspring: Exits

Venture capital returns are generated by successful exits. These are typically acquisitions or IPOs. For example, in 2002 Sequoia Capital provided early stage funding to the address book service company Plaxo. In 2008 it was acquired by Comcast. In 1999 Sequoia Capital invested seed money into the internet search engine Google. In 2004 it went public.

While both results did well for Sequoia, the Google IPO drove the performance of Sequoia VIII. Metrick and Yasuda (2011) define Sequoia VIII as a superstar fund (a fund which earned more than 10 times its committed capital, in this case $250 million). At the time of Google’s IPO, Sequoia VIII owned about 23.9 million shares which priced initially at $85 per share, provided Sequoia with over $2 billion in returns. This single investment provided over 8 times committed capital for Sequoia and its limited partners. Though the magnitude of this “home-run” is uncommon, the result is not. Cochrane (2005) and others show funds are typically made up of many failures, some reasonable successes (1 to 2 times committed capital) and the rare “home-run” investments which drive the returns.

That said, studies are ambivalent on the notion that venture capital can improve the post-exit performance of the portfolio companies. Florin (2005) develops a model of performance focused on how early funding decisions for firms that later completed an initial public offering will affect post-IPO performance. The author noted that during the

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8 Metrick and Yasuda also set a minimum of $50 million in committed capital to be considered for superstar status.

9 Taken from Google’s Form S-1.
1990’s, small firms going public appeared to have followed two different paths to high growth. Many were designed from inception to grow fast and secure necessary funds through IPO. Other older firms were redesigned to take advantage of the overheated IPO market. He finds that, in general, pre-IPO and post-IPO characteristics and performance were similar for firms with and without VC backing. Even with substantial venture backing (30% or more), post-IPO performance did not significantly improve.

Florin also notes that original founders of start-ups that undergo IPOs who use venture capital funding generated significantly less wealth for themselves and were less likely to remain as chief executive officer post-IPO. This suggests that entrepreneurs motivated primarily by wealth creation or control of their ventures should minimize VC backing when going public. VC backing is related to higher levels of funding until the IPO but not related to firm’s ability to grow and be profitable post-IPO. His study uses a sample of 277 IPOs from 1996, which calls into question how the information technology bubble effects fund performance.

Using data compiled from Venture Economics, Table 6 summarizes publicly disclosed venture capital exits post the I.T. Bubble. Less than half of the acquisitions which occurred during this time period disclosed values. On the other hand, concurrent with SEC regulations, all IPO performance data are publicly available.
Table 6: Venture Capital Exits Post Information Technology Bubble

This table shows the total value and average deal size for all successful exits in the venture capital industry. Columns 2 and 4 show the total acquisition value and IPO value with the number of deals in parentheses. Columns 3 and 5 show the average acquisition and IPO size. Source: Thomson Reuters.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total Acquisition Value (# of Deals)</th>
<th>Average Deal Size ($ millions)</th>
<th>Total IPO Value (# of Deals)</th>
<th>Average IPO Offer ($ millions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>$7496 (119)</td>
<td>$63</td>
<td>$2023 (29)</td>
<td>$70</td>
</tr>
<tr>
<td>2004</td>
<td>$16,044 (188)</td>
<td>$85</td>
<td>$11378 (94)</td>
<td>$121</td>
</tr>
<tr>
<td>2005</td>
<td>$30,862 (165)</td>
<td>$187</td>
<td>$4485 (57)</td>
<td>$79</td>
</tr>
<tr>
<td>2006</td>
<td>$16,694 (159)</td>
<td>$105</td>
<td>$5117 (57)</td>
<td>$90</td>
</tr>
<tr>
<td>2007</td>
<td>$28,201 (165)</td>
<td>$171</td>
<td>$10326 (86)</td>
<td>$120</td>
</tr>
<tr>
<td>2008</td>
<td>$14,100 (117)</td>
<td>$121</td>
<td>$470 (6)</td>
<td>$78</td>
</tr>
<tr>
<td>2009YTD</td>
<td>$4,436 (48)</td>
<td>$92</td>
<td>$1293 (8)</td>
<td>$162</td>
</tr>
</tbody>
</table>

Source: Thomson Reuters

Since less than half of acquisitions disclose values, estimating the returns to each fund is difficult. Since most venture capital investments are syndicated (Wright and Lockett 2003), this problem is compounded. Chapter 3 of this thesis sidesteps the calculation of fund level performance by focusing solely on the post-IPO performance of venture-backed companies.

In addition, the very definition of private equity implies that SEC regulations requiring performance reporting do not apply here. Thus both reported performance data and any constructed benchmark (for example: Cambridge Associates Venture Capital Index) suffer from various reporting biases. Even given these difficulties, several authors have recently estimated the private equity manager/venture capitalists’ return from private equity and venture capital investments (for example see Cochrane, 2001, and Ljungqvist and Richardson, 2003). These studies found that venture capital returns generated returns higher than public markets and these returns compensate for risk incurred.
In a discussion of private equity investing, Lerner et al. (2007) observe the returns generated from institutional investors’ capital allocated to private equity. Returns varied dramatically across institutional investor types. Endowments reported returns from their privately equity allocations substantially above average. Based on subsequent fund returns, endowments proved to be good at predicting fund manager success. The relative success is robust across various model specifications and does not show end point sensitivity. Endowments outperform other institutions across the different private equity subclasses.

Lerner et al. (2007) explore solutions to what they named the Limited Partner Performance Puzzle. They rule out performance driven by endowments’ allocation to intrinsically riskier funds. They also refute alternate objective functions (e.g. the need to invest in-state for pension funds) as the driver for the lower performing institutional investors. Finally, though they find some evidence that endowments’ relatively early interest in private equity allows for these investors access to the choice private equity firms, endowments and pensions outperform other institutional investors controlling for early entry in to the market.

Lerner et al (2007) suggest agency problems which drive certain institutional investors to make inferior fund selection. Misalignment of interests between Institutional Investors and their Principals results from high-turnover within the ranks of the investment professionals and poorly conceived compensation packages. Lerner et al. also speculate whether their findings can be generalized to other asset classes. In this work, I discover a third
substantial driver behind the disparity of performance, investment sophistication. Endowments employ a spread of quantitative and qualitative techniques absent from many other institutional investors. Even within the private pension funds, the second best performing subclass, investment techniques lag behind that of institutional investment professionals.

Venture capitalist firms invest with a strategy similar to that of small cap mutual funds. One important difference includes a longer period before exits can generate profits, usually at least 3-5 years. During this time there is no well-developed secondary market. Divesting firms deemed unprofitable is thus difficult and is usually accomplished by a write-off of the failure. The lack of well-developed secondary markets lends to the difficulty of accurately pricing the value of the assets of the companies within the fund.

For this reason and for the well-known upward bias of venture firms (due to not reporting poor-performing or dead firms) difficulties persist in accurately assessing the risks and performance of venture capital firms. One way to overcome this obstacle is to track the performance of publicly traded venture capital firms. Martin and Petty (1983) compare a modest set of venture capitalists (11) against growth-oriented mutual funds and the S&P 500. They use two methods, standard mean-variance analysis and an early version of stochastic dominance. Using buckets of varying risk-aversion (and risk-seeking) behavior, Martin and Petty show performance that indeed IPOs backed by venture capital perform with high degrees of risk and return. Much of the motivation for Chapter 3 of this
dissertation comes from Martin and Petty. In Chapter 3, an expanded data set of IPOs linked to specific characteristics of their parent VCs are tracked.

In summary, studies seem to indicate that, on average, returns may be little different than small cap public equity. However, the best firms do extremely well. For example, Metrick and Yasuda (2011) find that of the top-tier venture capital firms, many have multiple superstar fund status (recall a superstar fund is one which returns at least 10 times capital invested). Among the top tier, Matrix Partners, Kleiner Perkins each have two funds which returned more than 10 times capital committed and Sequoia has three funds with plus 10x returns.

1.5 Venture Capital and the Mean Variance Frontier

Increasingly, venture capital has been used to augment an institutional investor’s portfolio returns. Justification for this comes not only from the higher expected returns but to further diversify the portfolio, pushing out the mean-variance frontier. The justification for many institutional investors comes from the belief that venture capital will expand the mean-variance frontier of their portfolio. In this section, venture capital, as an asset class, is added to an ex-ante optimal portfolio. To test if the mean variance frontier is pushed outward, a Gibbons Ross Shanken (GRS) test of portfolio efficiency is employed (Gibbons et al., 1989).

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10 “Top-tier” is subjective, of course, with no concrete definition. Metrick and Yasuda define it as either consistent top-quartile and top-half performance or VC firms which can charge 30% carry (against the more typical 20%) as well as the presence of at least one superstar (10 times capital committed earned) fund and one star (5 times capital committed earned) fund. Fifteen firms made this list (Kleiner Perkins, Sequoia, Accel, Draper Fisher, Menlo Ventures, etc.)
Care must be taken when interpreting the results for multiple reasons. First, it will be shown that venture capital return distributions are not normally distributed. Also, the generated covariance matrix is based on historical performance. The underlying correlations are probably minimums, with no reason to believe that they will ever be less than the model assumes. Nevertheless, models similar to this have been used by institutional investors as one justification for venture capital in the portfolio.

1.5.1 Mean Variance Frontier: No Venture Capital

In this section, a baseline mean-variance frontier using an array of asset classes is generated. The frontier is based on a number of assumptions:

**Assumption 1:** Asset allocation is the primary predictor of returns.

I base this assumption off of the work done by Sharpe (1992), Brinson et al (1991) and others who show that asset allocation drives most of the performance of institutional investors. Brinson et al (1991) show that 91.5% of variation in investor performance is due to differences in allocation to Treasury Bills, long-term bonds and equity. Later studies show that when asset classes are expanded, the asset class selection accounts for even more of the variation.

**Assumption 2:** \( w_i \geq 0 \ \forall i \in (i \text{ asset classes}) \)

This assumption disallows a typical institutional investor from shorting asset classes. This is done to help align the model with the current Prudent Man Rule interpretations.
Assumption 3: $\sum w_i = 1$

This is the assumption that institutions are fully invested. It follows from Table 7, which show the average asset allocation of endowments from 2004-2010. Besides any leverage nested within some of the real estate funds and among independent return funds, there is assumed no explicit use of leverage. On average 5% assets were allocated to venture capital.

<table>
<thead>
<tr>
<th>Table 7: Endowment Asset Allocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Each column represents the average percent of allocation each asset class for all endowments in the NACUBO Study.</td>
</tr>
<tr>
<td>2004</td>
</tr>
<tr>
<td>Domestic Equity</td>
</tr>
<tr>
<td>International Equity</td>
</tr>
<tr>
<td>Fixed Income</td>
</tr>
<tr>
<td>Alternative Strategies (Venture Capital)</td>
</tr>
<tr>
<td>(3.1%)</td>
</tr>
<tr>
<td>Short-term/Cash</td>
</tr>
<tr>
<td># of Institutions Reporting</td>
</tr>
</tbody>
</table>

*From 2004-2007, the NACUBO Endowment Summaries do not distinguish between Domestic and International Equity.

Constraint 1: $w_{\text{Cash}} + w_{\text{Fixed Income}} \geq 0.10$.

This is a liquidity constraint, which states that, at any given time, allocation to Cash (Cash, Cash-Equivalents, Treasury Bills) plus the allocation to Fixed Income (here assumed to be a mix of mid-term and long-term domestic fixed income) must be at least 10% of the overall portfolio. This requirement is done to meet any liquidity needs of institutional investors such as pension funds, foundations and endowments.
**Constraint 2:** $w_{Cash} \leq 0.05$

This is the cash-drag constraint. It states that at any given time cash cannot comprise more than 5% of the portfolio. The long-run nature of the institutional investor implies that “prudent” include capital appreciation. This assumption is supported by the endowment allocations in Table 7. Even during the credit crisis of 2007-2009, there was never more than 5% of allocation to cash (endowments under $25 million did reach 9% allocation to cash in 2009).

<table>
<thead>
<tr>
<th>Asset Class</th>
<th>Representative Index</th>
<th>Historical Geometric Mean$^{11}$</th>
<th>Historical Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domestic Equity</td>
<td>S&amp;P 500</td>
<td>12.7%</td>
<td>16.6%</td>
</tr>
<tr>
<td>International Equity</td>
<td>MSCI EAFE</td>
<td>19.5%</td>
<td>20.1%</td>
</tr>
<tr>
<td>Fixed Income</td>
<td>Aggregate Bond Index</td>
<td>9.6%</td>
<td>8.3%</td>
</tr>
<tr>
<td>Independent Returns</td>
<td>Tremont Hedge Fund Universe</td>
<td>12.2%$^{12}$</td>
<td>8.6%</td>
</tr>
<tr>
<td>Real Assets</td>
<td>Custom Blend$^{13}$</td>
<td>13.3%</td>
<td>5.3%</td>
</tr>
<tr>
<td>Leveraged Buysouts</td>
<td>Thomson Financial Buyout Index</td>
<td>5.3%</td>
<td>11.5%</td>
</tr>
<tr>
<td>Cash</td>
<td>90 Day Treasury Bills</td>
<td>6.2%</td>
<td>1.8%</td>
</tr>
</tbody>
</table>

Sources: Cambridge Associates, NCREIF, CRSP, MSCI, Tremont

Table 8 describes the asset classes available to the institutional investor. Returns are adjusted for CPI (though it is common practice for endowments to adjust for HEPI, not CPI). The model adjusts independent returns downward in response to the bias noted in

$^{11}$ Net of historic inflation as calculated by CPI

$^{12}$ Corrected for backfill and survivorship bias using Malkiel and Saha (2005)

$^{13}$ 50% NCREIF, 25% S&P Oil and Gas, 25% NCREIF Timberland which reflects approximate allocations to real assets by foundations and endowments according to historical NACUBO studies
Malkiel (2005). It uses historical geometric means, as the effects of compounding should be included when describing the potential returns. The correlation matrix used in the optimizer is presented in Table 9. It is based on historical returns found in Table 8.

### Table 9: Correlation Matrix

This table shows the correlation matrix used to develop the covariance matrix for the derivation of the mean-variance frontier. Sources: See Table 8.

<table>
<thead>
<tr>
<th></th>
<th>Domestic Equity</th>
<th>International Equity</th>
<th>Fixed Income</th>
<th>Independent Returns</th>
<th>Real Assets</th>
<th>Buyouts</th>
<th>Cash</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domestic Equity</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>International Equity</td>
<td>0.75</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed Income</td>
<td>0.0014</td>
<td>0.00</td>
<td>-0.07</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Independent Returns</td>
<td>0.67</td>
<td>0.62</td>
<td>-0.19</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Real Assets</td>
<td>0.49</td>
<td>0.50</td>
<td>-0.07</td>
<td>0.51</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buyouts</td>
<td>0.20</td>
<td>0.27</td>
<td>-0.11</td>
<td>0.42</td>
<td>0.20</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Cash</td>
<td>0.09</td>
<td>0.10</td>
<td>0.57</td>
<td>0.07</td>
<td>0.10</td>
<td>0.06</td>
<td>1.00</td>
</tr>
</tbody>
</table>

The results, using a portfolio optimizer, are provided in Figure 6. The line traced from the risk-free rate (as defined by the 90 day Treasury Bill) to the point of tangency represents the optimal portfolio which is used as the benchmark portfolio for the GRS test.

### Figure 6: Mean-Variance Efficient Frontier

This figure shows the efficient frontier for an institutional investor, given the calibration and assumptions of the model, with a given risk-free rate and no venture capital access. Sources: See Table 8.

---

14 The 0.00 correlation is offsets: positive correlation from 1981-2000 and strong negative correlation from 2001-2009.
1.5.2 Venture Capital Return Distributions and Mean-Variance Analysis

Venture capital returns fail the standard tests for normality. See Table 10 for the results. For all tests employed, the data reject the normality of venture returns. In contrast, the tests all fail to reject the normality of the S&P 500 quarterly returns during the same time period.

<table>
<thead>
<tr>
<th>Test</th>
<th>Venture Capital</th>
<th>Domestic Equity (S&amp;P 500)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>W-stat</td>
<td>Prob&gt;</td>
</tr>
<tr>
<td>Shapiro-Wilk Test</td>
<td>.795</td>
<td>.00</td>
</tr>
<tr>
<td>Shapiro-Francia Test</td>
<td>.782</td>
<td>.00</td>
</tr>
<tr>
<td>Test for Skewness</td>
<td>.00</td>
<td>.06</td>
</tr>
<tr>
<td>Test for Kurtosis</td>
<td>.00</td>
<td>.22</td>
</tr>
</tbody>
</table>

Gibbons et al (1989) argue that as long as sample sizes are large enough (in this case 114 quarters of returns); the test is robust to misspecifications. However, Zhou (1993) shows that tests with non-normal return distributions will tend to over-reject the mean-variance efficiency of the ex-ante portfolio. Thus, institutional investors must be cautioned against over-interpretation of these results.

1.5.3 The Gibbons Ross Shanken Test

The GRS test of portfolio efficiency can be used to test if the addition of an asset (in this case an asset class, venture capital) pushes the mean-variance frontier outwards. The setup
for the test will be as follows: The factor portfolio will be the optimized portfolio described in section 1.5.1. It allows access to the following standard asset classes: domestic equity, international equity, independent returns (often referred to as Hedge Funds), real assets (real estate with energy and timber components, when the data allow), domestic fixed income, leveraged buyouts and cash. It is based on the following equation:

$$R_t - R_f = \alpha_i + \sum_{j=1}^{L} \beta_{ij} (F_{jt}) + \varepsilon_{it}, \quad i = 1 \ldots N$$

(1)

where

- $L - 1 = $ Number of Priced State Variables
- $F_{jt} = $ Excess return on the jth factor portfolio, here the ex ante optimized portfolio
- $R_t - R_f = $ Excess return on a portfolio with venture capital

If the factor portfolio is a mean-variance efficient portfolio, then $\alpha_i = 0$ for all $i$. The GRS test statistic can be expressed as a ratio of Sharpe ratios:

$$\left( \frac{T - N - L}{T - L - 1} \right) \left[ \frac{N + \hat{\theta}_{N+L}^2}{\sqrt{N + \hat{\theta}_L^2}} \right] - 1 \sim F(N, T - N - L)$$

(2)

where $T$ is the number of periods and $N$ is the number of test portfolios (in this case, $N = 1$). The maximum Sharpe ratio of the assets classes with no access to venture capital is denoted $\hat{\theta}_L$, while the maximum Sharpe ratio of the portfolio of assets which includes venture capital is $\hat{\theta}_{N+L}$. If the GRS statistic is sufficiently large, then the null hypothesis that $\alpha_i = 0$ can be rejected. The results of the GRS test are presented in Table 11.
The result from Table 11 rejects the null hypothesis that venture capital is completely spanned by other alternative asset classes. The results must be interpreted cautiously for at least two reasons. First, the non-normality of venture capital returns suggest that GRS statistic will tend to over-reject the null hypothesis that $\alpha_{VC} = 0$. Second, as shown in Table 7, endowments and institutions are nowhere near the 15% optimal VC exposure; the percentages have been trending upwards. The benefit may not be fully realized at these lower levels. Figure 7 shows the expanded mean-variance frontier (and subsequent higher Sharpe ratio) assuming a portfolio with “optimal” amounts of venture capital.

| GRS Test                  | GRS Statistic | P>|z|  |
|---------------------------|---------------|-------|
| Venture Capital (15%)     | 6.12          | .015  |

Table 11: Gibbons Ross Shanken Test
The following table shows the results of the GRS test when an ex-ante optimized portfolio is compared to one which is optimized with the inclusion of about 15% venture capital.

Figure 7: Mean-Variance Efficient Frontier with Venture Capital
This figure shows the efficient frontier for an institutional investor, given the calibration and assumptions of the model, with a given risk-free rate and venture capital access. Sources: See Table 8.
1.6 Conclusion

This chapter provides an introduction into the asset subclass known as venture capital. It focuses on what is known about the venture capital universe. It investigates a model similar to those used at institutions to justify the inclusion of venture in the portfolio. This chapter forms the basis of the theoretical work conducted in Chapter 2 as well as the empirical model tested in Chapter 3.
CHAPTER 2: THEORETICAL LIMITED PARTNERS SYNDICATES IN VENTURE CAPITAL FUNDING

Abstract

This chapter explores a syndication model for institutional investors with respect to venture capital commitments. Institutional investors, such as endowments, pensions, and foundations, act as limited partners formally committing capital to venture capital funds, often syndicating their investments with other institutional investors. This syndication can occur when one investor is offered a portion of a follow-on venture fund in which the investor may choose to either retain the entire portion of the fund or bring aboard other investors, thereby reducing the original investor’s commitment in the fund. This chapter establishes the rationale behind this practice.
2.1 Introduction

This chapter presents a syndication model for institutional investors with respect to venture capital commitments. Institutional investors, such as endowments (e.g. Princeton University, Yale University as well as smaller colleges and Universities), pensions (e.g. CalPERS and Pennsylvania Public School Employees’ Retirement System) and foundations (e.g. Robert Woods Johnson Foundation) act as limited partners (LPs) formally committing capital to venture capital funds. These LPs often syndicate their investments with other institutional investors. The procedure is often as follows: University A is offered a $10 million piece of a follow-on venture fund. The university may retain a $10 million piece or it may suggest to the venture fund that it bring in Universities B and C to make $2.5 million commitments thereby reducing University A’s commitment to $5 million. This chapter explores the rationale behind this syndication.

Here I define the general partner (GP) as the venture capital fund manager. GPs include venture capitalists such as Sequoia Partners, Oak Investments and General Catalyst Partners. GPs run the venture capital funds. This includes raising capital from LPs, discovering potential investments in entrepreneurs, sourcing staged financing to these entrepreneurs and generating profits by exiting from ownership from these entrepreneurs. Venture capital exits usually come in the form of Initial Public Offerings (IPOs) of the portfolio companies, acquisitions by other firms or write-offs.
The syndication that is discussed here is among limited partners and it is based on quid pro
quo behavior by the other members of the syndicate. Syndication may also occur among
LPs to alleviate information asymmetry that exists between limited partners and venture
capital general partners. The motivation for such a study stems from information asymmetry that is present when investing in private equity. Before exploring this asymmetry the study will establish the rationale behind an institution’s desire to fund venture capital as a part of that institution’s portfolio.

2.1.1 Rationale for the Presence of Venture Capital in the Institution’s Portfolio

Private Equity, specifically venture capital, builds companies with equity funding, and therefore carries with it equity risk. The nature of an entrepreneurial venture is itself highly risky, with failure usually implying a write-off of all invested capital. Since risk must be rewarded with return, it follows that high expected returns should be the primary rationale for venture capital in the portfolio of an institutional investor.

However, Moskowitz and Vissing-Jorgensen (2004) call a glaring lack of these high returns the “Private Equity Premium Puzzle.” They suggest that returns should be higher than experienced for the level of volatility that exists within private equity. Within the asset subclass of venture capital, the lack of diversity within the general partner’s portfolio does not justify the marginal premium offered by its returns. When Moskowitz and Vissing-Jorgensen correct for survivorship and reporting biases, no real premium from investing within this portfolio subclass remains.
Returns, then, may not be a sufficient rationale for investment. However, the diversification private equity provides within an institutional investor’s portfolio may provide sufficient conditions for inclusion. Most large institutional investors build portfolios principally on the notion of asset allocation. For example, the Princeton University’s endowment allocates its resources to the following asset classes: Domestic Equity, International Developed Markets, International Emerging Markets, Real Assets (with subclasses Real Estate, Energy and Timber), Private Equity (Leveraged Buyouts and Venture Capital), Fixed Income and Cash. When developing models of asset allocation, the institutional investor will typically estimate the correlations (and therefore covariances) between asset classes. The more sophisticated institutional investors (e.g., endowments) will build covariance tables for use in mean-variance optimizers.

Private Equity, specifically venture capital, shows low correlation with most other asset classes. Now these correlations must be read with caution. Private Equity is not marked to market so the correlations carry far less meaning than marked to market asset classes. The results are interesting. Using data provided by Cambridge Associates, the study develops a correlation matrix. Please see Chapter 1 for full details. A summary is presented here. Annual returns, real and nominal, were compared, but only real, adjusted by the CPI are reported here. Cambridge Associates provide end-to-end net returns to limited partners for both venture capital and leveraged buyouts (referred to as “Private Equity). Returns from venture capital date to vintage year 1981 and returns from leveraged buyouts date to 1986.

15 Source: 2006 Princeton University Investment Company Annual Report
Returns from domestic equity (represented by the S&P 500) were correlated with venture capital at only .48. Against international equity, represented by the MSCI EAFE, the correlation drops to .33. Correlation ranges between .03 and .15 with the various real assets tested (real estate, timber and energy indices). In fact, there is only one asset class which generates a degree of correlation of .5 or greater. Independent returns (“hedge funds”) show a .61 correlation with venture capital returns.

Venture capital offers diversification possibilities for debt as well. Returns from venture capital generate significantly low correlations with domestic fixed income (-.10), and cash (.05), represented by Treasury bill returns. Thus, even against the evidence provided the Private Equity Premium Puzzle, venture capital exposure within a portfolio may act as an excellent source of diversification.

2.1.2 Private Equity Information Asymmetry

The very nature of private equity precludes transparent information flow to potential investors. The ability of the limited partner to discern the quality of the venture capitalist, and then send a credible signal is difficult. Private Equity firms are not required to file performance results for their portfolio companies with the Securities and Exchange Commission. Thus any sort of performance report a general partner does elect to publicly present may show signs of bias. This holds true for most asset classes which do not file with the SEC. For example, Malkiel and Saha (2005) show that this voluntary reporting, combined with backfill bias and survivorship bias, greatly skews the results reported from another non-SEC filing asset class, hedge funds.
In addition, Blaydon and Horvath (2002-2) show that the venture capital industry lacks an agreed upon valuation standard for portfolio companies. They document cases of substantial difference in company values from one VC firm to another. Though venture capital fund managers regularly complain about the lack of standard valuation techniques, there are no standardized valuation models that all GPs adhere to according to Blaydon and Horvath (2002-1). Thus any portfolio company valuations reported by the GPs are highly suspect and not credible from the standpoint of potential investors.

2.2 Syndication

This study argues here that syndication, defined as an association of firms which invest to promote a common interest, will be a vehicle by which a limited partner maximizes its expected risk-adjusted returns when investing in an asset class. Syndication among private equity firms, notably venture capital, has been well-documented. The combined effort and cumulative knowledge of a venture capital syndicate should have an effect on the overall quality of the entrepreneurs produced. Likewise, this study extends the idea of syndication to institutional investors, which provide financing to the venture capitalist firms themselves. Before presenting this, it will be helpful to establish the utility of syndication among the venture capital GPs.
2.2.1 Syndication in Private Equity

Syndicates of venture capital firms exist in the private equity world for a number of reasons. Brander, Amit and Antweiler (2002) study the behavior of venture capital general partners. They find that there exist at least two reasons for syndication among venture capitalists: “an informative second opinion” and “managerial value-add.” Analogously, given the role most limited partners play with respect to their general partners—finance first, advice and counsel second, “an informative second opinion” justifies institutional investor syndication. The syndicating LP wants to bring in a skilled new investor.

Evidence of the need for informative second opinions comes from Gompers (1996). He shows that under-established venture capitalists are compelled to take inefficient actions to establish/enhance reputations and increase the size of subsequent funds (and ease the fundraising process). They will bring a portfolio company public before the optimal time. This sort of behavior, called grandstanding, allows the general partner to establish a track record of completed IPOs even though returns from going public suffer premature sale in the public market. A syndication of limited partners, with each limited partner management team adding its own set of due diligence techniques, will be more likely to recognize and punish a grandstanding venture capitalist (e.g., by threatening to not commit to future funds). Thus, the LPs will be better off after a syndicate is formed.

This paper is devoted to studying conditions for limited partner syndication. The impetus for this research started from recognizing that most general partners also syndicate their
investments to their portfolio companies. Wright and Lockett (2003) show that nearly two-thirds of all United States venture capital investments had more than one general partner participating in the financing. According to Brander, Amit and Antweiler (2002), three-fifths of Canadian venture capital investments have historically had more than one venture capital firm contributing. This paper hypothesized that LP may also use syndication as both a signaling mechanism as a source of an informed second opinion from other skilled limited partners.

2.2.2 Limited Partner Syndication

While no former study has established the opportunity for limited partners to syndicate, evidence abounds. There is considerable research (e.g., Sias 2004), both theoretical and empirical, on groups of limited partners investing as herds. Institutional herding manifests itself in investment decisions enacted to avoid being called, in the words of Keynes (1936) “eccentric, unconventional and rash” by their peers. Though these money managers act in a potentially inefficient manner, within the light of agency problems, this behavior is rational from their point of view. The decision of the manager to follow the behavior of others often ignores material information that ought to be considered.

Considerable work has been done studying the behavior of the group of investors known as the institutional investors. This includes work on the behavior of these investors as a group. Irrational behaviors within the public market, such as herding, have a strong theoretical framework. Recent studies [Grinblatt and Titman (1989, 1993), Grinblatt,

Herding is considered an irrational behavior to the detriment of the limited partners and their investments alike. This paper begins with a behavior that is also seemingly irrational at first glance. Once explored, however, syndication is shown to be a mutually beneficial signaling mechanism that is entirely rational and efficient from both the point of view of the limited partners. Agency problems should not be present with syndication, as the model predicts that it will be in the best interest of a skilled limited partner to syndicate if it views the decision to do so within the context of long-run investing.

Sias (2004) shows that demand for a security is positively correlated with demand for the security during the previous period. He attributes this to institutional investors following each other into and out of the same securities. In other words, he argues that that institutions herd as a result of inferring information from each other’s trades (Yale commits to Fund XYZ, Princeton infers that this is a good investment and follows suit). The model assumes an absolute positive correlation between the returns generated in the previous time period (Fund I) and future commitments (Fund II).

The substantial difference in investment approaches across institutional investor subclasses compound these asymmetries. Lerner, Schoar and Wongsunwai (2007) suggest that agency problems drive certain institutional investors to make inferior fund selections.
Misalignment of interests between Institutional Investors and their Principals results from high-turnover within the ranks of the investment professionals and poorly conceived compensation packages. Lerner et al. also speculate whether their findings can be generalized to other asset classes. This study proposes a third substantial driver behind the disparity of performance: investment sophistication. Endowments, with the highest median returns, may employ a spread of quantitative and qualitative techniques absent from many other institutional investors.

In addition, a survey of the array of conferences offered to institutional investors suggests an atmosphere more conducive to cooperation than competition. The Institutional Investors Education Foundations coordinates the annual forums to bring together “experienced, sophisticated investors with industry, government and academic experts to share their specialized knowledge and experience (www.iief.org).” The Opal Group, which has the motto “Your link to investment education,” hosts educational conferences for a wide array of institutional investors. Raymond James and Associates hosts an annual Institutional Investors conference. A review of these and other conferences suggests an atmosphere that is driven as much by cooperation as competition. Contrast this with conferences designed specifically for mutual fund managers. Conferences for mutual fund managers do bring competitors together, but the focus is on education—for example, new regulatory requirements. The draw to these conferences is not to “share their specialized knowledge and experience.”
In this model, the limited partners motivate syndication by offering a portion of their pro-rata allocation to a follow-on fund, assuming the first venture capital fund was successful. Ultimately, the general partners of the fund select which organizations have access to the funds. Generally, syndication is allowed. However, if the general partners disallow such a syndicate to form, then the model would no longer apply. Presumably at this point, the limited partner would continue to invest at the pro-rata rate, as it is assumed to be a profit maximizing entity.

2.2.3 Incentives to Syndicate

This chapter focuses on competition and cooperation among LPs as well as the relationship between LPs and their GP. Using a signaling game in which the LP’s payoff depends on both the equilibrium signal and the LP’s skill level, the study shows that syndication in a subsequent round of fundraising can be used as a credible signaling device. The signal is used by the institutional investor to communicate private information about its fund-selection ability, and more importantly, its quality as an investment partner. After the initial capital commitment to the venture capital fund, the institutional investor becomes informed about its ability to select high-quality venture capital funds by observing the quality of the fund in which it invested. It then sends a costly (and thus credible) signal by giving up a piece of follow-on fund and syndicating with other skilled limited partners. This signal occurs from a reduction in the pro-rata size of its commitment to the successful VC’s follow-on fund.
This signal, based on the current expected return of the portfolio, is necessarily costly. As will be shown below, the cost comes in the form of reduced current expected returns to the LP since it has reduced its exposure to the GP. It forfeits a portion of its ownership in the follow-on fund (and all subsequent funds) to allow for other high ability institutional investors to join the fund. It buys, through this forfeiture, a series of benefits.

Multiple rationales exist for this seemingly inefficient behavior. The first is the notion of quid pro quo. Consider a limited partner with access to a high-quality venture capital fund. Call this institutional investor limited partner A (LP_A). LP_A believes that access to one of its high-quality venture capital funds will elicit an in-kind response by some limited partner B (LP_B); i.e., LP_B allows LP_A access to one of its gem VCs. If the expected payoff of access to LP_B’s VC funds exceeds the loss from syndication this behavior is justified. This quid pro quo justification will be modeled as a profit maximizing equilibrium with expected quid pro quo gains exceeding expected current losses (from reduced exposure) for skilled investors. Deviation from syndication (and hence mutual access to high-quality funds) is punished with a response of no further syndication from other beneficial partners.

A second rationale comes in the form of overall reduction in risk to the signaling institutional investor. A second LP brings its own experience, due diligence and monitoring
to the venture capitalist’s follow-on fund. It frees up capital which can be invested in other investment vehicles, thus further diversifying the syndicating limited partner’s portfolio.\textsuperscript{16}

Syndication mitigates multiple forms of risk. First, an experienced limited partner’s due diligence process is quite extensive. A syndication of limited partners will each have a unique approach to due diligence. Syndication will therefore minimize the probability that the high-quality venture capitalist follow-on funds will be of low quality.

A syndicated investment also limits overexposure due to a project’s scale. The size of most endowments, foundations and pensions makes it theoretically possible to supply sufficient capital for most private equity endeavors. This is especially true when observing venture capital fund size. However, this risks over-exposure to the idiosyncratic risk of a particular general partner. Syndication provides proper scaling to the general partner and allows for proper risk-sharing for the limited partners. The limited partner still bears the weight of systematic risk of the asset subclass, but idiosyncratic risk at the fund level is reduced.

Third, syndication reduces agency problems that may arise if the general partner does not put forth proper effort to maximize returns for the current fund. This may occur if the general partner spends too much of his time raising capital for follow-on funds. Coordinated withdrawal of future funding by a syndicate of limited partners can act as a credible threat to non-performing general partners. In other words, while the hazard of one

\textsuperscript{16} While the cause of diversification does not hinder the effect of the signal, the reduction in commitment to the high-quality venture capital firm cannot be to invest in another commitment with higher expected returns. This would negate the costly nature of the signal and relinquish any credibility.
limited partner foregoing a future commitment of capital to a VC’s follow-on fund may aid in the proper alignment of interest, the pressure for good behavior on the part of the GP intensifies when it is answerable to a group of limited partners. The general partner will have a more difficult time raising new capital if an entire syndicate of investors withdraws. Thus, syndication reduces the risk of the general partner not putting forth proper effort towards its portfolio companies.

The final rationale for syndication is more subtle and will chiefly benefit smaller limited partners who may be investing in venture capital for the first time.\footnote{Why syndication helps smaller LPs will be discussed in detail in a subsequent section.} It is based on the need to signal ability to other established venture capitalists in which the LP may wish to invest in the future. Syndication arises from the difficulty many smaller limited partners face in getting access to the top-tier VC firms. While public markets display a great deal of price efficiency, the very nature of private markets suggests potential inefficiencies. There is a marked difference between the returns in the top quartile of VC firms and the rest of the VC universe. These “top-tier” venture capitalists have funds that are oversubscribed as presented by Swenson (1999).

Drawing on data from Cambridge Associates, one of few reputable databases on private equity funds (the others include Thompson Venture Economics and Standard and Poor’s Capital IQ), there is marked difference between upper quartile returns and the median return. The venture capital data are from 1,277 U.S. VC funds with vintage years ranging from 1981 to 2008. The private equity (i.e. buyouts) data features 787 U.S. buyout funds.
As per the recommendation of Cambridge Associates, vintage years 2005-2008 are dropped. Funds from these years are too new to produce any significant returns. The data are compiled below, in Table 1.

<table>
<thead>
<tr>
<th></th>
<th>VC Upper Quartile vs. Median</th>
<th>VC Median vs. Lower Quartile</th>
<th>Buyouts Upper Quartile vs. Median</th>
<th>Buyouts Median vs. Lower Quartile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Difference in Returns</td>
<td>14.00%</td>
<td>8.82%</td>
<td>8.43%</td>
<td>8.32%</td>
</tr>
</tbody>
</table>

The average upper quartile venture capital fund can be expected to earn returns 14% higher than the median VC fund, averaging across vintage years. Given the potential for reporting bias, the difference between the Median and Lower Quartile is probably understated. Thus, the desire to invest in upper quartile returns is intense, more so than the publicly traded counterpart. VC selection helps avoid catastrophic returns from lower quartile funds.

Cambridge Associates also publishes the returns across vintage years from buyout firms (which Cambridge Associates calls Private Equity), see Table 1. The difference between upper quartile buyout funds and median buyout funds is also substantial, though not as large in absolute value. This difference could be the impetus for further study into signaling among buyout firms as well.

This difference in returns leads to excess demand for access to the top-tier VC firms. Top-tier VC funds are typically oversubscribed with many limited partners locked out.
Hochberg et al (2009) show that over-subscription is correlated with the success of the funds themselves. Thus limited partners are highly motivated to get into would-be oversubscribed VC funds.

The difference in upper quartile and median returns is large and upper quartile venture capital firms show performance persistence across funds. Even controlling for the quality of the IPO market and the mechanical overlap that occurs when a venture capitalist uses newer funds to continue financing investments from older funds, evidence suggests performance persistence, especially among the top performers. Kaplan and Schoar (2005) show performance persistence over different funds of the same VC firm using internal rate of return as well as total value to paid-in capital measures. Hochberg et al (2009) provide further evidence that the data support the prediction of performance persistence among venture capital firms. Hochberg et al (2007), while presenting the benefits of venture capital networks find that fund exit rates are positively related to VC firm experience and the IPO or acquisition exit rate of the previous fund. Thus it is in the best interest of the limited partner to gain access to these oversubscribed venture capital funds.

The rationale for syndication rests on the belief that the current cost of syndication (decreased current expected returns) will be out-weighed by the increase in access to other top-tier venture capital firms (increased future expected returns). Syndication is thus comparable to a publicly traded firm’s decision to retain some of its earnings at the cost of dividends. If this move causes the increase in the PVGO (Present Value of Growth Opportunities) to exceed the loss in current asset value, then the price of the company’s
stock should increase. Analogously, syndication results if the limited partner’s future expected returns (≈ PVGO) exceed the loss from suboptimal current capital allocations (≈ Current Value of non-growth assets).

The rationale for syndication does not rest on traditional capital constraints. For example, most pensions and some college endowments have the capacity to fund, in theory, all but the largest VC firms, especially a VC firm raising money for its second fund (which will typically be at least as large as the first fund).

However, other capital issues may force a limited partner to syndicate. For example, syndication may occur to avoid overexposure to certain idiosyncratic risks (defined here as the investment skills of the general partners) or certain systematic risks (over exposure to the asset class of Private Equity). This paper does not address this issue, focusing solely on the signaling aspect of syndication.

When the original institutional investor attempts to syndicate, it is done in the hopes to create a consortium of other high-ability institutional investors. A syndicate of high-ability limited partners conveys a number of advantages. For example, a group of skilled limited partners are less likely to engage irrational behavior that force venture capitalists to make myopic decisions on the GP’s portfolio companies (e.g., threatening the withholding of future commitments if the long-run nature of the venture capital cycle is not fully understood).
To recap, the decision to syndicate rests on four rationales. First, if $LP_A$ grants access to a high-quality venture capital follow-on fund, $LP_B$ may grant, quid pro quo, access to some of its future high-quality venture capital funds. Second, $LP_A$ has a vested interest in an informed second opinion which may occur through syndication. Thus syndication will reduce the idiosyncratic risk which comes from committing large amounts of capital to a few venture capital investments. Finally, $LP_A$ may use syndication as a method to credibly signal its quality to oversubscribed top-tier venture capitalists.

2.2.4 Signaling by Syndication

Little theoretical framework has been laid for institutional investments in the private market. This paper develops one aspect of information sharing: syndication. Syndication among institutional investors is also used as a credible signal of high-quality to potential future over-subscribed top-tier venture capital funds.

In this model, institutional investors are grouped into several clusters. The motivation to cluster into groups such as large, private universities and state pension funds is based on two reasons. First it allows the model to net out some of the fixed effects and characteristics that are consistent across institutions such as the role the Prudent Man Clause (See Chapter 1 for a discussion of this) plays in investment decisions. Second, the groupings presumably maximize the probability of syndication as there tends to be more intra-cluster communication and employment crossover than there is inter-cluster communication and crossover.
Lerner, Schoar and Wongsunwai (2007) show empirically that institutional investors’ returns on private equity vary greatly across asset subclasses. Endowments perform the best with excess IRR across all private equity funds of 30.6%\(^{18}\) (perhaps because they have lesser liquidity needs and therefore hold more illiquid investments). Wealth advisors overall perform second best with an excess IRR of 16.5%. Public pension funds and Insurance companies follow with excess IRRs of 8.9% and 8.3%. Corporate pension funds and banks/finance companies have the lowest excess IRRs of 4.1% and -0.2%. Breaking private equity into the asset subclasses of early-stage venture capital, later-stage venture capital and buyouts yields similar institutional investor rankings. It should be noted that almost all excess IRR vanishes across institutional investors within the buyout asset subclass. This paper ignores this asset subclass and focuses on venture capital only.

Lerner, Schoar and Wongsunwai (2007) explore solutions to this puzzle, known as the limited partner Performance Puzzle. They rule out performance driven by endowments’ allocation to intrinsically riskier funds. They also refute alternate objective functions (e.g., the need to invest in-state for pension funds vs. the freedom to do otherwise) as the driver for the lower performing institutional investors. Finally, they find no evidence that endowments’ relatively early interest in private equity allows for these investors access to the choice private equity firms.

\(^{18}\) Where Excess IRR is the IRR of the asset sub-class minus the median IRR from a portfolio created from the total funds formed every year, from 1991 to 1998.
The difference across these institutional investors could partly be explained by syndication. Investors observe, formally or informally, the movements of lead limited partners within their asset classes and modify their subsequent investment decisions.

The limited partners of Fund I determine if the fund was high-quality or low-quality based on their observations of ongoing Fund I; thus limited partners operate from a position of information asymmetry with respect to the rest of the market. While ex ante predictions on the quality of the money manager are based on information that is by definition incomplete, the LP will have a strong sense as to whether or not Fund I will be a success relative to other funds of the same vintage year.

This observation occurs at some point leading up to the end of Fund I. Thus, institutional investors such as endowments and private pension funds cannot credibly announce that they are skilled (the skill set mentioned above) to general partners. Thus, there is no credible flow of information from the buy side (the limited partners) to the sell side (the general partners), as final return data are not yet available. When general partners decide on which institutional investors to approach for capital, they are at an information deficit. If they are a well-established venture firm, they may be selective as to which limited partners are offered space on the fund thus avoiding certain “unknown” limited partners.

There are several risks to working with an unknown (or unsophisticated limited partner). The following is developed from the cases contained in Lerner, Hardymon and Leamon
(2004). For example, consider public pension funds, which tend to report returns close to the median of all institutional investors. Though these returns are near the median, they do have a high degree of standard deviation. The authors theorize that turnover rates and poor governance (political appointees dominate the investment boards of many public pension funds—these directors frequently have little understanding of Private Equity). From the point of view of the general partner, having a sophisticated investor in your portfolio implies that your fund is more likely to be successful, ex ante. Sophistication can be sorted by institution type, which yields some difference in returns to LPs (and thus difference in carried interest to GPs) according to Lerner et al (2007).

It is in the best interest of any GP to partner with high-quality, long-term focused institutional investors. It is also in the best interest of less-experienced LPs to be a part of a consortium of skilled institutional investors. The hope is for easier access in the future to other top-tier venture capitalists. The GPs of the top-tier VCs now have a “vetted” source of skilled LPs. In this study, the mechanism through which this occurs is a signal.

Signaling is explored in Gertner et al (1988). This paper takes a different approach. The considerable effects of herding are ignored, instead using syndication as a method of increased access to top-tier general partners (through signaling these GPs and quid pro quo from the syndicate of LPs), rather than endogenized behavior. The signal is used to differentiate between skilled limited partners and unskilled limited partners.
“Skilled” is defined here by a set of desirable characteristics, from the point of view of the venture capitalist. First, skilled implies that the institutional investor’s focus is long-run and will ignore the short-run write-downs, or turbulent IPO markets. While most funds require a lock-up period of 3-5 years in their subscription documents, an unskilled LP who does not understand the nature of venture capital can apply significant pressures to GPs to generate premature returns, which could lead to premature exits, known in the industry as grandstanding. The literature shows that grandstanding will reduce the final value of the portfolio companies and thus lower the expected returns of the LPs.

“Skilled” implies that the institutional investor’s due diligence for its existing VC investments is accurate. This suggests an ability to select investments that will produce high (relative to the median, as previously discussed) expected returns and provide sage counsel to the VCs during the investment process. Both the institutional investor’s skill at due diligence and its value-add as a partner represents desirable characteristics for any venture capitalist.

Thus the institutional investor could signal “skilled,” through syndication to outside, over-subscribed, top-tier venture capitalists. The signal must be credible and must occur as early as possible to maximize the probability of gaining access to these other top-tier venture capital firms. To be credible, it must be costly (otherwise, all limited partners would send such a signal). Syndication can be one such method. When a limited partner purposefully under-allocates resources to a follow-on fund, instead offering a portion of the follow-on fund to a fellow institutional investor, it is costly as the immediate expected payoff is
reduced. The syndication will naturally be with an institutional investor which is already perceived as highly skilled, at least to the original limited partner. The limited partner may try to syndicate with an institutional investor who is currently invested with one or more top-tier venture capital firms.

2.3 Model

This model considers a venture capital firm which successfully raises its Fund I from a single, probably inexperienced limited partner. These restrictions are placed on the model without complete loss of generality (though later it will be shown that an inexperienced limited partner will benefit more from syndication than an experienced limited partner). The model can be applied to already syndicated groups of limited partners, by focusing on the behavior of one limited partner and ignoring the other LPs, though the incentives for further syndication are reduced.

This study develops a model of syndication. A lead limited partner (denoted $LP_A$) reduces commitments to a successful follow-on venture capital fund and offers one or more additional institutional investor(s) room to commit capital. The framework relies on several assumptions regarding limited partners. First, there is considerable information asymmetry built into the model. It exists between the limited partners and the general partner. Even with a prospectus and extensive due diligence can base amount of uncertainty about the quality of the GP as well as the probability of success remain. In addition, there is also information asymmetry between the limited partner and outside top-
tier venture capital firms. The signaling modeled here should be read as credible and therefore reduces this information asymmetry.

A second assumption to the model is the extended lock-up period of Private Equity. Years before all entrepreneurial exits occur general partners will begin fundraising for follow-on funds. This usually means that limited partners commit to follow-on funds raised by the general partners before original commitments have been fully realized. Though the final results are unknown, this does imply that the limited partners will have material non-public information regarding the probable success of the fund. This private information forms the basis of syndication.

Finally, the model assumes that limited partners will observe only the behavior of limited partners within their asset subclass (endowments have most contact with other endowments; pension fund managers attend pension fund conferences). While it is likely that pension funds may observe the behavior of endowments, it is assumed that the limited partners only observe behavior within their own asset subclasses. Any inter-asset class variations can be ignored; focus solely on Institutional Investor behavior.

In this model there will be a lead institutional investor (limited partner A). This limited partner A (\(LP_A\)) can be either skilled (patient, steady-hand, long-term vision, broader understanding of risk, deeper understanding of the Private Equity asset class) or unskilled in its ability to select and invest in venture capital funds (the operators are referred to as general partners, or GPs). At time \(t=0\), \(LP_A\) commits capital to GP’s Fund I. As of this
time, $LP_A$ may not know if it is skilled or unskilled. The limited partner monitors the performance of the general partner from time $t=0$ to $t=1$. This Fund I may have some exits by $t=1$, but it will not be fully liquidated. But even if there are no exits, $LP_A$ will have a good idea how the portfolio companies are progressing.

At time $t=1$, $LP_A$ discovers if it is skilled or not based on the expected relative performance of the GP. This information is private, provided to the LP by the GP. At time $t=1$, the general partner begins to raise capital for a follow on fund (Fund II). The limited partner will typically be granted at least a pro-rata share of this follow-on fund. The limited partner, however, recognizing the benefits of syndication, will reduce its commitment to Fund II, offering some portion to another institutional investor (referred to as $LP_B$) perceived to be skilled.

An unskilled limited partner will not engage in syndication for a number of reasons. As will be shown later, the unskilled limited partner will have a lower optimal level of effort as well as lower returns from its effort, which will affect future expected returns for the unskilled LPs portfolio. These reductions will keep the unskilled LPs from pooling with the skilled LPs.

In equilibrium, only a skilled limited partner would be willing to undertake this costly syndication; a skilled $LP_A$ expects higher gains from the benefits (quid pro quo access to $LP_B$’s venture capital funds, greater future access to other top-tier venture capitalists) to

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19 This makes sense since most venture capital portfolio companies are held at cost until the time of their exit.
offset the losses to the current expected value of the portfolio. The model generates predictions that are consistent with empirical evidence about the performance of syndicated investments, as well as the behavior of institutional investors of similar size and goals. (Brander et al.)

The rationale for such a theoretical framework is not readily apparent. First, consider an institution such the Commonfund. The Commonfund is an investment firm committed to pooling the capital of various small institutional investors (pensions, endowments and other non-profits), providing professional investment services to these institutional investors and providing their clients with an array of investment vehicles. Though venture capital and private equity are significant parts of the Commonfund’s asset allocation, typical applicants to the Commonfund do not have access to these venture capital funds. In fact, the application process limits the typical new institutional investor to more traditional asset classes, not even offering new access to Commonfund’s Hedge fund.

Independent of Commonfund, syndication may be a way to increase access to venture capital for smaller institutional investors. However, the rationale for syndication seems ostensibly counter-intuitive. First, consider that capital flows follow good performance: a limited partner which skillfully selected a high-ability VC fund may choose to voluntarily share information with other investors and, more importantly, reduce its share in what is expected to be a valuable follow-on fund. This necessarily implies a smaller than optimal capital allocation to the follow-on fund and therefore lower current expected returns.
In addition, manager compensation is often measured against the average compensation of the institutional investor’s peers as well as performance relative to its peers. Typically base management compensation is pegged to average peer institution compensation. Thus, it is in the best interest of the LP to have syndicate partners which do well, in the long-run. In the short-run, the effects are different. Bonuses, however, may be tied to performance relative to peers\textsuperscript{20}. Thus, why would a management team wish to permit and encourage a competitor to access what is quite probably a new “diamond in the rough” venture capital fund? In the short-run, syndication will surely lower the effort of the limited partner management team and thus the expected return from any worthwhile venture capital investment. The total effect of syndication should be negative for the current payoff (as bonuses are tied to relative peer performance) and positive for future payoffs (as base salaries get increased along with average peer compensation).

2.3.1 Signaling Game

The model uses the signaling game first developed by Spence (1973, 1974) to distinguish between skilled limited partners and unskilled limited partners. The model begins with a sole limited partner A ($LP_A$) which commits capital to Fund I of a venture capitalist of unknown quality (setting the fund’s vintage year to $t = 0$). From $t=0$ to $t=1$ the general partners use this capital to form a series of commitments usually in the form of staged financing to a portfolio of entrepreneurs. During this time, the general partner will report

\textsuperscript{20} For example, the Princeton University Investment Company ties its employee compensation to performance relative to a 3-year rolling average of peer performance as well as its target asset allocation benchmarks.
on progress to the limited partners, allowing LP_A to assess the probability that the fund will be successful as well as the magnitude of this success. Thus, by t = 1, the quality of the VC is known with some probability to the LP as either high-ability or low-ability. This information is not public at this point, as the gains made by Fund I have yet to be realized.

The limited partners may begin making additional capital commitments to the subsequent Fund II (with vintage year t = 1). Once Fund II is raised the general partner will allocate capital in a similar manner, committing capital to entrepreneurs from time t=1 to t=2. At time t=2 capital and any profits from Fund I are returned to LP_A. In addition, the general partner’s quality is revealed through Fund II to any new limited partners not initially committed to Fund I, though this is irrelevant to the model, as syndication will have occurred before t = 2. Finally, the model predicts that LP_A’s quality will be revealed, through syndication, by t=2.

Of course venture capital funds do not mature and return capital to limited partners in two years, thus the move from t=0 to t=1 is, with almost certain probability, greater than one year. The same logic holds for time t=1 to t=2. These periods are normalized though to retain the use of the phrase “vintage year.”

In this model, the entrepreneurs are amalgamated into a portfolio that can either be High or Low Performing, but this is not known until at least one period after the fund is formed. The model works as follows:

- At t = 0, a lead limited partner (LP_A) invests in the general partner
\begin{itemize}
  \item From $t = 0$ to $t = 1$ LP\textsubscript{A} learns of the probable quality of the general partner investments.
  
  \item At $t = 1$, the LP\textsubscript{A} concludes whether the general partner is High or Low ability. The general partner begins raising capital for Fund II. The decisions for the LP\textsubscript{A} to participate and to syndicate occur at this time.
  
  \item At $t = 2$, Fund I returns all capital, Fund II participants learn if the general partner is High or Low quality, though the model has $t = 2$ as the endpoint.
\end{itemize}

2.3.2 The Institutional Investor

The institutional investor serves several important functions. First, as a member of the “buy-side,” it selects to whom capital is committed at time $= 0$. The ability to select a high-quality venture capitalist is based on the LP\textsubscript{A} skill set, which is at this point unknown, even to the LP\textsubscript{A}. The unknown skill level can be either skilled (S) or unskilled (U). The LP\textsubscript{A} is skilled with probability $\theta$. Let,

\begin{align*}
  k_0 &= \text{Committed Capital, Fund I} \\
  k_1 &= \text{Committed Capital, Fund II} \\
  v_H &= \text{Final Value of VC Commitment (funds I and II), Conditional on a successful GP fund and High ability GP} \\
  v_L &= \text{Final Value of VC Commitment (funds I and II), Conditional on a successful GP fund and Low ability GP}
\end{align*}
\[ \sigma_H = \text{Standard Deviation of VC Commitment (funds I and II), Conditional on a successful GP fund and High ability GP} \]

\[ \sigma_L = \text{Standard Deviation of VC Commitment (funds I and II), Conditional on a successful GP fund and Low ability GP} \]

**Assumption 1:** Conditional on a successful fund, \[ \frac{v_H - k_1}{\sigma_H} > \frac{v_L - k_1}{\sigma_L} > 0 \text{ and } v_L > k_0 \] (1)

This assumption tells two things. First, the venture capital performance is positively related to the abilities of the venture capitalist, on a risk adjusted basis. Second, it assumes that even the low-skilled VC, if successful, should be able to raise a follow-on fund.

Institutional investors are assumed risk neutral and commit sufficient funds to allow the VC to fully invest in all portfolio companies. Also, if the VC provides positive returns to its LP(s), then the VC will be able to raise the second fund from at least these LP(s).

In this model, the limited partner acts as a fund of funds; one of its primary functions is the selection of general partners. The model begins with the selection of a general partner at time = 0. The limited partner’s ability to select a high-quality general partner is not known at the beginning and the limited partner can be skilled (S) or unskilled (U) with probability \( \theta \). An institutional investor with selection skills is more likely to recognize a high quality (H) VC or low quality (L) during the due diligence process. Let:

\[ p_s = \text{Pr}(v = v_H \mid S) \text{ and } p_u = \text{Pr}(v = v_H \mid U) \] (2)
Assumption 2 quantifies the selection skills of limited partners:

**Assumption 2:**

\[
p_x = \Pr(v = v_H \mid S) > p_u = \Pr(v = v_H \mid U)
\]

(3)

Now turn to the probability that the limited partner is skilled, updated on its ability to select a high quality venture capital firm. From updated performance reports and cash distributions, \(LP_A\) ascertains the ability of the general partner during the maturation of Fund I (sometime between \(t = 0\) and \(t = 1\)). It then revises its beliefs about its own fund selection skills. Bayes’ rule results in new probabilities based on the perceived abilities of general partners. Using Bayes’ rule, the updated probabilities are:

\[
\theta_H = \Pr(S \mid H) = \frac{P(H \mid S)\Pr(S)}{P(H \mid S)\Pr(S) + P(H \mid U)\Pr(U)}
\]

(4)

\[
= \frac{p_x \theta}{p_x \theta + p_u (1 - \theta)}
\]

Similarly:

\[
\theta_L = \Pr(S \mid L) = \frac{P(L \mid S)\Pr(S)}{P(L \mid S)\Pr(S) + P(L \mid U)\Pr(U)}
\]

(5)

\[
= \frac{(1 - p_x)\theta}{(1 - p_x)\theta + (1 - p_u)(1 - \theta)}
\]

**Assumption 3:** \(\theta_H > \theta_L\)  
See the appendix for proof of this proposition.

This states that the probability that the limited partner is skilled is greater if the limited partner selected a High Quality VC at \(t = 0\). As of \(t = 1\), Fund I has not fully exited. Thus, the information is only known to \(LP_A\) and not observable to other institutional investors or other general partners. The performance is verifiable, of course, since after fund I
liquidates, its performance will be known. But until that time, LP_A possesses valuable private information about its selection ability, which it uses as the determinant of its skill level—skilled (S) or unskilled (U).

2.3.3 Limited Partners: Effort, Cost and Expected Utility

In a traditional education signaling model, \( e = \) level of education. Here \( e \) will be the effort put forth by the limited partner with respect to the venture capitalist. Effort can be advice and counsel provided to the general partner regarding its portfolio of entrepreneurs. It can be quantified empirically by time spent in contact with the general partners or by the limited partners serving on the Board of some of the general partners’ portfolio companies.

The probability of a successful fund is correlated with the effort put forth by the fund’s limited partners. Let \( p(e_i) = \) Probability of a successful VC fund given the effort level \( e \) and LP type \( i \). This function has the following characteristics:

\[
\begin{align*}
p'(e_i) &> 0 \\
p''(e_i) &\leq 0
\end{align*}
\]

Through advice, an informed second opinion and a “steady-hand” investment strategy, the LP can help increase the fund’s success. This increase in the limited partner’s effort is with decreasing marginal productivity.
**Assumption 4:** For any given level of effort, $\bar{e}$:

$$p(\bar{e}_H) > p(\bar{e}_L)$$

This assumption states that for any given level of effort, the high-quality limited partner will increase the probability of the venture fund success more than an unskilled limited partner’s similar effort. Likewise, the limited partner cost is a function of effort, $e$, with the following properties:

- $C(e) \geq 0 \quad \forall e$
- $C'(e) > 0$
- $C''(e) \geq 0$

This effort occurs between period markers $t = 0$ and $t = 1$ but before the general partners ability is revealed to $LP_A$. Effort is costly, and it takes time away from the other functions of the $LP_A$ (such as monitoring other investments, considering new investments, preparing annual reports and due diligence on potential investments). For simplicity in the derivations cost function is normalized such that $c(e) = e$.

Let $\gamma = \text{the percent of profits secured by the GP, known as the performance fee}$. Here the variable has range of $0 < \gamma < 1$. Typically, performance fees will range between 20% and 30% of profits, with most around 25%, according to Gompers and Lerner (1999).

For simplicity, the study ignores the management fee (the fixed fee charged to the LP by the GP for management of committed capital). This fee lowers the value of the limited partners committed capital monotonically, and thus should not affect the behavior of either
the limited partner or the VC once capital is committed, at least relative to other venture
capital firms. Of course, $1 - \gamma$ is the returned capital, net of performance fee.

Finally, institutional investors will presumably hold well-diversified portfolios across
multiple asset classes. Their utility is therefore a function of risk-adjusted returns (typically
calculated using the Sharpe ratio) rather than returns alone. The utility function will be
expressed in terms of risk-adjusted returns

Any fund in which the limited partner is not syndicated will yield the following payoff,
which is contingent on the success of the venture capital fund (see the Appendix for the
derivation):

$$U_{LPA} = \Phi[p(e_i)\Gamma_j] - e \text{ for } i \in [U, S], j \in [H, L], v_j \neq 0$$

where $\Phi = 1 - \gamma$ and $\Gamma_j = \frac{v_j - k_i}{\sigma_j}$. This utility function $U$ is in risk-adjusted returns and
expresses the expected difference in the LPs overall utility as a result of committing some
portion of its overall fund to the GP’s Fund I.

2.3.4 General Partners

The general partners of a venture capital firm will invest a percentage of their personal
capital to a fund. This is done both to increase their own potential returns (and reduce
incidence of personal taxes) and to show that their interests are aligned with those of the
limited partners. This will be a small percentage of the overall fund size, typically 1% of
the overall capital raised (VCexperts, 2010). Other than the assumption that the general partner’s interests are aligned and wish to maximize profits, this capital contribution is ignored for the sake of model simplicity.

General partners will do a series of fundraisings in which they reach out to multiple capital sources. In this model, it is assumed that LP_A will recommend LP_B to the general partner as a part of the fundraising process. This is not an unrealistic assumption; it is in the best interest of the general partner to seek out multiple capital commitments. Offering a portion of the follow-on fund is ultimately the decision of the general partners and the mechanism for that will be in the section on the syndication partner.

It is assumed, also for simplicity, that this fund is the first fund by the general partner. This is not a necessary condition as most general partners prefer a mix of at least a few limited partners (they are not putting all their capital commitment eggs in one basket). In addition, a general partner would be reluctant to yield their fund’s entire capital space to a new LP_A in lieu of any original investors. In addition, if it is not the VC’s first fund, then there is the ability to observe previous funds, creating a prior set of beliefs about the venture capitalist’s ability levels. Though it is possible to build a model with a prior on the general partner’s ability level, it makes derivation unnecessarily complicated and is ignored in favor of focusing on the main issue, the separating equilibrium.

This model contains three distinct dates with two periods of observation. In t=0, Fund I receives capital from an initial limited partner investor, LP_A. While it is not necessary for
the structure of the model to limit the number of initial investors to one limited partner, it allows the focus to be on the interaction with any new limited partners in the subsequent fund. It yields, in t=2, either 0 or $v_j$, with probability of each outcome determined by the quality of the general partner. Fund I yields a value depending on the quality of the venture capitalist.

**Assumption 4:** $v_H > v_{med} > v_L$

If Fund I yields $v_H$, then the internal rate of return generated by its cash flows exceeds the median internal rate of return\(^{21}\) of the universe of funds for that vintage year. If Fund I yields $v_L$, its internal rate of return is below that median internal rate of return. Thus it follows that

$$v_H > v_{med} > v_L.$$ 

The general partner is a high quality firm when the random variable $v$ yields 0 or $v_H$. Likewise if the general partner is of lesser quality, $v$ will yield 0 or $v_L$. Note that $v$ represents the total value of the fund, not the total value of the venture capital Firm.

This paper predicts the relationship between the limited partner and the decision to syndicate during the fundraising for Fund II in $t = 1$. At $t = 1$, the lead limited partner must decide two things. It first must choose whether or not to invest in the follow on fund, Fund

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\(^{21}\) The universe of venture capital funds displays a high degree of kurtosis, thus the median is better than mean as a representation of average.
II. Second, it must decide whether or not to allow other limited partners access to the fund by lowering its share of capital commitments (to some $z_A < 1$).

It is often the case that a general partner will use subsequent funds as a way to provide additional financing to entrepreneurs from previous funds. Reasoning can be both rational (to carry a potentially successful entrepreneur’s firm through difficult times or to get the firm to a successful future exit) and irrational (to continue to fund a low quality entrepreneur to avoid a write-off, even if the probability of success is low). No distinction is made between portfolio companies which have additional rounds of funding from Fund II. Only the overall rate of return is important in this analysis.

For simplicity, there are no assumptions regarding the role of the entrepreneurs within each fund. The model assumes that the portfolio will either return overall results that generate an internal rate of return above the median (hence $v_H$) or below the median (and thus $v_L$).

2.3.5 Sequential Syndication

Syndication can occur in the model during the capitalization of Fund II. $LP_A$ invites one (or more) additional limited partner (named $LP_B$) to commit capital $k_B$ at time $t = 1$. In return, the lead $LP_A$ forfeits a fraction of $v$, denoted $s$ to $LP_B$. Let $s =$ the percentage of any fund given up to a syndicate partner. Similarly, any fund that is syndicated will have a current expected payoff of:

$$U_{LP_A}^S = (1 - s)\Phi[p(e_j)\Gamma_j] - e \text{ for } i \in [U, S], j \in [H, L], v_j \neq 0$$
It is important to distinguish between the LP\textsubscript{A}’s desire to signal skilled to oversubscribed top tier VCs versus alternate objectives. For example, the investor may desire to free cash for alternate asset allocation or alternative commitments to other venture capitalists. To distinguish this, the expected value of the venture capitalist’s Fund II must be greater than the utility obtained from these alternate investment opportunities. Prior to the decision to syndicate, LP\textsubscript{A} has allocated its resources optimally according to its expectations.

This eliminates the decision to syndicate as a Pareto improving decision; rather it forces the decision to be costly. Keep in mind that ultimately LP\textsubscript{A} hopes to access limited space on upper-quartile VC funds either through the new syndicate partner \(LP_{B}\) or because top-tier venture capital firms now recognize LP\textsubscript{A} as a skilled investor, and skilled implies a patient, knowledgeable, and therefore desirable partner. That long-run objective is considered exogenous at this point.

Likewise, the assumption that LP\textsubscript{B} invests the full amount offered by LP\textsubscript{A} is not a necessary condition. The key is the forfeiture of some materially significant portion of Fund II. To make the signal credible, LP\textsubscript{A} must suffer a loss in current expected returns. LP\textsubscript{A} decreases its exposure to the VC of known high-quality and thus causes LP\textsubscript{A}’s overall expected returns to decrease. Thus, the signal is costly and therefore credible.

2.3.6 Rationale for Separation

If the GP’s Fund I is unsuccessful then the limited partners would choose not to invest in the follow-on fund. No separation can be obtained as limited partner will have no indicator
of manager selection skill. If fund is successful, what would induce skilled limited partners to syndicate while preventing unskilled partners from pooling with their skilled peers? The rationale for syndication comes from balancing current losses with future potential gains.

If Fund I is successful and most likely generate risk adjusted returns above the median ($\Gamma_{\mu}$), then the limited partner is considered skilled and will attempt syndication. The discounted future benefits generated from syndication (reciprocity from the syndicate, access to top tier venture capital funds) outweigh the immediate loss from reduced exposure to Fund II. Reduced exposure to Fund II can be expected, ex ante, to reduce the risk-adjusted value of the investment portfolio since it now has a higher probability of success, according to research on fund performance persistence (recall Kaplan and Schoar (2005) or Hochberg et al (2009)).

If Fund I is somewhat successful but will most likely generate risk-adjusted returns less than the median fund ($\Gamma_{\lambda}$), then the limited partner is considered unskilled. The discounted future benefits are less certain than in the case of skilled LP. The unskilled limited partner may have little confidence in its ability to generate future returns based on either its skills in selecting the better managers in the broader set of funds offered to it as well as its fund monitoring skills. Given its success with Fund I, though mediocre, the unskilled limited partners realizes that it is better to maintain the pro-rata allotment to Fund II than to risk
relying on its skills as a manager selector to increase future returns. Thus, the unskilled
limited partner chooses not to syndicate.22

2.3.7 Syndicate Partner

Any potential syndicate partner, LP_B, is assumed to have a similar cost of effort function.
If the general partners of the fund believe LP_B is a skilled limited partner, then they can
grant access to the follow-on fund. If allowed a share of the follow-on fund, LP_B is
believed to be skilled by both Limited Partner A and the general partners of the fund.

If the investment is syndicated at time 1, so that the syndication partner receives a fraction s
of the project, then the syndicate’s payoff in the event of success becomes:

\[ U_{LPB} = \Phi s p(e_B) \Gamma_j - c_p(e) \quad \text{for} \quad j \in [L, H], s \in (0, 1) \]

**Assumption 5:** Syndicate limited partner B has non-negative expected values (otherwise
they would not invest).

2.4 The Signaling Game: Current and Future Payoffs

By \( t = 1 \), the ability to select high quality venture capitalists is revealed to the limited
partner. A skilled LP_A wishes to use this information to convey this information to top-tier
venture capitalists to increase the probability of access to these VCs’ future funds. The

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22 Alternatively, it can be argued that the unskilled partner would have an even stronger incentive to syndicate, as it would want
access to the selection abilities of older, more skillful limited partners. This presents an interesting game theory puzzle—if
the unskilled limited partner successfully fools a syndicate partner for Fund II, the deception should reveal itself quickly
(assuming no significant learning-by-doing during Fund II. Even if this were to occur, it probably indicates that the Limited
Partner was skilled in the first place.)
device used to signal is the fraction \( s \) offered to \( LP_B \) (i.e. any future institutional investor) for participation in Fund II. Presumably, \( LP_A \) believes that \( LP_B \) is a skilled institutional investor. \( LP_B \) is presumably a well-known or well-established limited partner. Perhaps \( LP_B \) has access to some of these top-tier VC that \( LP_A \) wishes to signal. This quid pro quo behavior is a driving rationale behind syndication, as explained in an earlier section, and can be the basis for a mutually profitable arrangement.

Fixing \( k_1 \), it follows that the larger the fraction \( s \), the higher the cost to \( LP_A \) since there is currently no other alternative investment with at least as high an expected outcome, which is given by assumption. Hence, \( LP_B \) receives an attractively-priced security, since the project’s expected value exceeds its cost, \( k_1 \). Thus, under-pricing is directly proportional to the size of \( s \).

2.4.1 The Current Payoff

\( LP_A \)’s decision to syndicate is now based on a cost-benefit analysis of two moving components. First, it must consider the current payoff; that is the loss of expected returns from the reduced exposure to the high-quality VC’s Fund II. Given that effort is costly, there should be a set of equations that solve for optimal effort allocation for the limited partner. The limited partner must consider other components of its portfolio and syndication is feasible.

Now turn to the effect of syndication on current effort put forth by the limited partners. When the limited partner chooses to decrease its share of ownership in Fund II it
necessarily lowers its current portfolio’s expected return. Lower expected returns imply lower expected limited partner management compensation by way of bonuses (see Section 2.3). Lowered compensation decreases the optimal level of effort put forth by the managers which leads to the following lemma:

**Lemma I:**
If syndication is feasible, then it strictly reduces the limited partner’s optimal effort.

See Appendix for proof.

The model assumes away any changes in due diligence resulting from the sharing of information from limited partner B’s due diligence since the direction of the effect should be the same. Alternatively, a syndicated limited partner, faced with increased aggregate due diligence (from the efforts of the other members of the syndicate) would not increase its own current level of due diligence. The optimal level of LP$_A$’s due diligence might be expected to fall when other sources of information are introduced, though the total diligence may well rise.

Now that some rules have been established with respect to the current payoffs, consider the utility function which must be maximized. Assumption 3 shows that a skilled limited partner is more likely to select high-ability venture capitalists while unskilled limited partners are likely to select low-ability venture capitalists. The syndication model collapses if, at time $t=1$, it is discovered that the GP was of low ability. Therefore, consider the case of high-ability venture capitalist. If syndication is feasible, and if attention is restricted to
the binary choice of “Unskilled” or “Skilled” limited partners, then the utility function must be one of the following four possibilities:

**Skilled, Syndicated.** Limited partner A’s choice maximizes the following equation:

$$\max_{e_i} p(e_i) \phi[(1 - s) \Gamma_H] - e_i$$

Taking the first order condition of this objective function, it is solved for its maximum.

Denote the solution: \(e^*_S\), and it solves this first order condition:

$$p'(e^*_S) = \frac{1}{\phi[(1 - s) \Gamma_H]}$$

The second order condition for a maximum follows from the fact that the probability function, \(p(e_i)\), is non-convex.

**Skilled, Not Syndicated:** limited partner A’s choice maximizes the following equation.

$$\max_{e_i} p(e_i) \phi[\Gamma_H] - e_i$$

Denote the solution \(e^*_S\), again with first order condition:

$$p'(e^*_S) = \frac{1}{\phi[\Gamma_H]}$$

**Unskilled, Syndicated.** Limited partner A’s choice maximizes the following equation:

$$\max_{e_i} p(e_i) \phi[(1 - s) \Gamma_H] - e_i$$

Denote the solution \(e^*_U\), again with first order condition:

$$p'(e^*_U) = \frac{1}{\Phi[(1 - s) \Gamma_H]}$$
Unskilled, No Syndication. Limited partner A’s choice maximizes the following equation:

\[ \max_e p(e_i) \phi[\Gamma_H] - e_i \]

Denote the solution \( e_U^N \), again with first order condition:

\[ p'(e_U^N) = \frac{1}{\phi[\Gamma_H]} \]

These results confirm Lemma 1. Holding project quality constant, the reduction \( s \) reduces the limited partner’s interest in VC Fund II. A smaller stake implies a lower expected payoff. In addition, a reduced allocation to Fund II reduces the limited partner’s effort in counseling and assisting the general partner and therefore lowers expected returns, ceteris paribus. Since \( p'(\ast) \) is non-increasing in \( e \), then since the FOC of the syndication exceeds the FOC no syndication in both the skilled and unskilled cases, the effort put forth from no syndication must at least as large.

Lemma II:

Regardless of syndication level, skilled limited partners exert more effort than unskilled limited partners. See the Appendix for Proof.

Consider now the implications of these results in light of Lemma 2. The probability of success is a concave increasing function in effort. Conditional on syndication, higher marginal benefit of effort implies a higher effort level by the skilled investor, since \( p'(e_U^S) > p'(e_U^N) \). Likewise, conditional on no syndication, the first order conditions
suggest that the skilled limited partner’s effort yielded a higher return, and thus puts forth more effort.

Consider the difference in effort exerted by skilled and unskilled limited partners. Compensation is an increasing function of performance and performance is an increasing function in effort. It follows naturally whether or not the limited partner syndicates that Lemma 2 should hold.

The Future Payoff

The loss of current expected returns is compared to the gains (if any) in exposure to other top-tier VC firms for future funds due to the signal sent as well as the skill level of LP_A. This is the future payoff that is derived from and is a function of both the actual skill level (skilled and unskilled) and the skill level signaled (syndicate or no syndicate). The future payoff can be described as:

\[ w_i^j = \sum_{t=2}^{\infty} d_t (\Phi p(e_i)(\Gamma_{i,j,t}) - e) \text{ for } i \in [U,S], j \in [Y,N] \]

where \( w_i^j \) is the sum of the present value of all future risk-adjusted returns generated by the limited partner’s commitments to venture capital. The \( d_t \) represents the discount rate of future cash flows. For simplicity, the model assumes similar discount rates across institutional investor types.\(^{23}\) The term \( \Gamma_{i,j,t} \) represents the expected future risk-adjusted

\(^{23}\) Recall the model assumes that endowments will be compared with endowments, pension funds with pension funds, etc. Given the similarities in investment style and investment horizon, a single discount rate should not be too unrealistic.
value of venture capital with respect to the limited partner. It begins in time $t = 2$ since the
decision to syndicate happens at $t = 1$. It is a function of both the skill level of the limited
partner (which only the limited truly knows) as well as the limited partner’s skill signal (the
decision to syndicate and thus signal “skill”). Notice that the decision to syndicate is now
endogenized into the payoff variable (where at time $t = 0$ it was not). If syndicated, the
future payoff increases due to the “quid pro quo” and access to top-tier venture capitalists.
The following matrix represents the payoffs:

<table>
<thead>
<tr>
<th></th>
<th>Syndication</th>
<th>No Syndication</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skilled limited partner</td>
<td>$w^Y_s$</td>
<td>$w^N_s$</td>
</tr>
<tr>
<td>Unskilled limited partner</td>
<td>$w^Y_u$</td>
<td>$w^N_u$</td>
</tr>
</tbody>
</table>

**Assumption 6:** $w^Y_s > w^Y_u$ for $i \in \{Y, N\}$.

Ceteris paribus, it follows that a skilled limited partner would have higher expected gains
for future investments in private equity for a number of reasons. First, a skilled LP will
tend to benefit from its thoughtful approach to investing. This holds whether the limited
partner syndicates or does not syndicate. And since compensation is related to
performance, it follows that $w^Y_s > w^Y_u$ and $w^N_s > w^N_u$.

**Assumption 7:** $w^Y_i > w^N_i$ for $i \in \{S, U\}$.

If top-tier venture capital firms view a limited partner as highly skilled, regardless of their
actual ability, there will be greater access to future fundraising efforts. If an unskilled
investor signals high-ability, top-tier VC’s will allow access to their future funds in the
same way they would to a skilled investor who signals high-ability. A syndicating LP_A has an even bigger incentive to syndicate to a skilled LP_B. LP_B offers a larger quid pro quo and will help the GP more than an unskilled LP. Thus, it follows that \( w^*_{S} > w^*_S \) and \( w^*_U > w^*_U \). In reality, though, if all investors pooled into syndications (both unskilled and skilled alike) then these top-tier VC firms could rationally assume that the signal is meaningless and ignore it. This assumption builds the payoffs and forms incentive compatibility constraints.

Let \( \Delta_S = w^*_S - w^*_S \) and \( \Delta_U = w^*_U - w^*_U \). Consider the following important assumption:

**Assumption 8:** \( \Delta_S > \Delta_U \) for any size \( s \) signal.

This assumption is necessary for a separating equilibrium to exist. It states that the skilled limited partner’s increase in value from syndication exceeds the increase in unskilled partner’s increase in value from signaling. Recall that syndication provides two ways to access top-tier venture capital funds—through the quid pro quo actions undertaken by limited partner B and through the costly signal of syndication itself. Without these assumptions, a separating equilibrium is not possible, since sending the signal is less costly for the unskilled investors. This is a consequence of the nature of the signal; it is a fraction of the VC Fund II and \( s\Delta_U < s\Delta_S \) for all \( s \). The increase in payoff from the signal must be large enough; otherwise the skilled limited partner would never undertake such an action, since it is more costly to do so. Thus, the equilibrium is a function of both the signal sent and the sender’s true type.
Since compensation is tied to performance and performance is a function of the skill level of the general partner, a separating equilibrium can occur, depending on the difference in future expected returns from a portfolio with and a portfolio without access to top-tier venture capitalists. As discussed previously, the difference between the top-tier venture firms and the rest of the universe is remarkable, making general partner selection an important skill to possess by limited partners.

2.4.2 The Separating Equilibrium

Turn now to defining the separating equilibrium and theorizing on the conditions necessary for this to occur. The definition must include a binary function governing the conditions under which the limited partner syndicates. In addition, conditions must be present such that LP_B (the syndicate partner) will have a positive expected profit, to induce LP_B to change its current investment allocations. Now, let

\[
\Lambda_i(s) = [ p(e_i^N) \phi[\Gamma_H] - e_i^N ] - \left[ p(e_i^Y) \phi(1 - s)(\Gamma_H) \right] - e_i^Y \] for \( i \in [S, U] \)

and recall that \( \Delta_i = w_i^Y - w_i^N \) for \( i \in [S, U] \)

**Definition I:**

A separating equilibrium consists of a fraction \( s^* \) and a set of beliefs \( \mu \) about the limited partner by outside top-tier VC firms such that:

1. Syndication signals a high type.

\[
\mu(S) = \Pr(S \mid Y) = \begin{cases} 
0 & \text{if } s < s^* \\
1 & \text{if } s \geq s^*
\end{cases}
\]
2. The skilled LP prefers to syndicate if the expected future payoff exceeds the current loss from syndication. Likewise, the unskilled investor does not benefit enough to syndicate.

\[ \Delta_s > \Lambda_s(s^*) \]

and

\[ \Delta_u < \Lambda_u(s^*) \]

Here, the \( \Delta_i \) represents the future payoff expected gains from syndication for LP\(_A\). These gains result from quid pro quo access to LP\(_B\)’s high-quality venture funds, the informed second opinion about future commitments from LP\(_B\) and the skilled signal sent to other top-tier VC funds. \( \Lambda_i(s^*) \) represents the current expected payoff losses from syndication.

This definition suggests that there is some costly reduction in current payoff which is greater than potential future payoffs for unskilled limited partners. This induces these limited partners to decline syndication and instead commit capital to the new fund equal to the pro-rata share. On the other hand this costly reduction increases the future payoff of skilled limited partners to such a degree that they separate from the pooled behavior of pro-rata commitments and instead syndicate.

Now consider values of syndication which will be acceptable by both LP\(_A\) and LP\(_B\). In other words, what value of \( s \) will induce the syndicate partner, LP\(_B\), to invest in the project, yet satisfy Definition 1. If access is too small, LP\(_A\) benefits from a smaller decrease in the current payoff but this case is ruled out as it will result in a negative expected gain for LP\(_B\).
If LP_A relinquishes too much of the fund to LP_B then it reduces the incentive to provide counsel and support to the general partner and this will decrease the expected value of the payoff, again resulting in negative profits to the syndicate partner (unless total monitoring effort increases or LP_B is particularly skilled in monitoring). Thus the value of s must fall in between a minimum and maximum value.

Denote this minimum and maximum as $s_{min}$ and $s_{max}$. The minimum value solves the following equation: 

$$s_{min} = \frac{c_B(e)}{\Phi(p(e_S)\Gamma_H)}.$$ 

Likewise, the maximum value solves 

$$s_{max} = \frac{\Phi[p(e_S)\Gamma_H] - e}{\Phi[p(e_S)\Gamma_H]}.$$ 

Any value of s outside of this will result in either non-compliance by the potential syndicate partner, who must be lured away from its already presumably optimal allocation or so syndication, if the share forfeited by LP_A is too high.

The second part of Definition 1 will benefit from some algebraic manipulation. Rearranging the terms such that the future payoffs are on the left side of the equation and the current payoffs on the right side yield some useful results. It shows that for a separating equilibrium to occur at $s^*$ then the gain from the future payoff $w^s_s - w^s_i$ must exceed the loss from the current payoff for the skilled limited partner. In addition, for the unskilled limited partner not to signal as well, the gain from its signal $w^s_i - w^s_u$ must not exceed the loss from syndication.
Now, the model establishes that the skilled investor has a cost that is higher to signal than the unskilled investor. This is necessary for the credulity of the signal. The cost associated with the loss of current payoff must be large enough to show to top-tier VC firms that the limited partner is serious about gaining access to their future funds.

**Lemma 3:** The syndication cost function, \( \Lambda_i(s) \), is increasing and concave in \( s \).

See Appendix for Proof.

**Lemma 4:** For the syndication cost function \( \Lambda \), the following is true:

1. \( \frac{\delta \Lambda_s(s)}{\delta s} > \frac{\delta \Lambda_u(s)}{\delta s} \)
and
2. \( \Lambda_s(s) > \Lambda_u(s) \forall \text{ feasible values of } s \)

See Appendix for Proof.

It is now time to establish the primary proposition of this chapter—the conditions necessary for a separating equilibrium to occur. The increase in future expected returns results from expectations of access to better quality venture capital funds (either directly from LP_B or indirectly through the signaling mechanism). Recall that the increase in the future payoff for the skilled investor exceeds the current payoff loss if the minimum level of syndication is used. In other words: \( \Delta_s > \Lambda_s(s_{\text{min}}) \). Also, the maximum amount of syndication, \( s_{\text{max}} \), dissuades the unskilled limited partners from pooling. In other words: \( \Delta_U < \Lambda_U(s_{\text{max}}) \).

Also, let \( s_s \) be the minimum signal such that the skilled \( LP_A \) syndicates: \( \Delta_s \geq \Lambda_s(s_s) \).
Finally let $s_U$ be the minimum signal such that an unskilled $LP_A$ syndicates: $\Delta_U \geq \Lambda_U(s_U)$.

**Proposition 1.** A separating equilibrium, with a unique solution in which only a skilled limited partner, $LP_A$ syndicates with at least one other limited partner, $LP_B$, exists if the following two conditions hold for the feasible set of $s \in (s_{min}, s_{max})$:

1. $s_U \geq s_{min}$ and $\Delta_S > \Lambda_S(s_U)$ or $s_U < s_{min} < s_S$
2. $\Delta_U < \Lambda_U(s_{max})$;

This implies one of two unique solutions:

1. If $s_U \geq s_{min}$ the unique separating equilibrium is $s^* = s_U$. This fulfills the Cho-Kreps Intuitive Criterion, with a consequent belief system that $\theta(H) = 1$ if and only if $s > s^*$. Any share relinquished greater than $s^*$ will decrease the total expected value of the unskilled limited partner.
2. If $s_U < s_{min}$, then the unique equilibrium is $s^* = s_{min}$. This fulfills the Cho-Kreps Intuitive Criterion, with a consequent belief system that $\theta(H) = 1$ if and only if $s \geq s_{min}$.

See the Appendix for proof.

This proposition implies both a border solution and an interior solution depending on the relationship of $s_{min}$ and $s_U$. If $s_U \geq s_{min}$, then the unique separating equilibrium is the interior solution $s^* = s_U$. This is according to the Cho-Kreps Intuitive Criterion. Thus,
any syndication with at least $s_U$ of Fund II relinquished to LP$_B$ credibly implies that it is in the best interest of LP$_A$ to syndicate.

On the other hand, if $s_U < s_{\text{min}}$, then $s_{\text{min}}$ is the unique solution, as enough of the follow-on fund is offered to LP$_B$ to induce it to syndicate with LP$_A$. At the same time, this $s_{\text{min}}$ is too large to increase the expected returns of unskilled limited partners ($s_U < s_{\text{min}}$, and expected returns are decreasing with shares given up). It is entirely credible to these outside, top-tier VC firms that LP$_A$ is a skilled investor and thus is a coveted partner for future funds.

Consider the following graphical representation of the current and future payoffs. The size of the signal, $s$, is represented horizontally. The magnitude of the loss of current payoffs is represented vertically as a function of the size of the signal. The loss functions of both the skilled and the unskilled limited partners are derived. The loss functions come out of the origin, as a signal of 0% would cause the function to collapse to zero.

Here the future gain functions, $\Delta_S$ and $\Delta_U$, are both given exogenously, as a magnitude of gains is all that is necessary to derive the central conclusions of Proposition 1. In a later section, the explicit function is presented for increased future payoff. For now, without loss of generality, assume constant changes in future payoffs. The size of the future gains relies only on the credibility of the signal, not the signal’s size.
2.4.3 The Outside Payoff

Here the model defines the outside payoff that must occur given a separating equilibrium. The results are derived from the point of view of the expected future payoffs of the limited partner. The model rests on the following assumptions. First, LP_A expects no other material changes to its asset allocation. While rebalancing, strategic tilts and tactical changes are a part of the investment plan of any sophisticated management team; they will be ignored here in favor of model simplification.

The limited partner will face the same investment opportunities as they faced at t = 0. In other words, the expected return from the limited partner’s allocations does not change from present to future. While unrealistic, this is done to simplify the model and derive the important conclusions from the results. To keep the model simple, it ignores the question of “future signals.”
Second, the study ignores any other potential changes in the investment portfolio. It is as if the same field of opportunities which existed at \( t = 0 \) exist at \( t = 1 \) (and beyond). This includes investment opportunities. It also includes no changes to the asset allocation decision as well as any current strategic tilts. For example, a long-run asset allocation plan may be an allocation of 40% of the portfolio to domestic equity, 20% to international equity, 20% to fixed income and 20% to private equity. However, the management team may believe that in the current investment climate international equity is more attractively priced compared to fixed income. Thus, they may strategically tilt 5% of their portfolio’s exposure away from fixed income into international equity. Finally, each asset class and individual money manager has expected values that have not changed. Thus, the investment landscape is fundamentally the same at \( t = 0 \) as when the limited partner decides to syndicate (\( t = 1 \)). The following payoffs LP\( \Lambda \) expects from its private equity portfolio based on the probability that the GP was high and low quality, recognized at \( t = 1 \).

\[
\begin{align*}
u_s &= \theta_H \{ p(e^H_s) [\phi \frac{v_H - k_1}{\sigma_H}] + (1 - p(e^H_s)) [\phi \frac{v_L - k_1}{\sigma_L}] - e^H_s \} + \\
&\quad (1 - \theta_H) \{ p(e^N_s) \phi \frac{v_L - k_1}{\sigma_L} + (1 - p(e^N_s)) \phi \frac{v_H - k_1}{\sigma_H} - e^N_s \}
\end{align*}
\]

\[
\begin{align*}
u_U &= \theta_L \{ p(e^H_u) [\phi \frac{v_H - k_1}{\sigma_H}] + (1 - p(e^H_u)) [\phi \frac{v_L - k_1}{\sigma_L}] - e^H_u \} + \\
&\quad (1 - \theta_L) \{ p(e^N_u) \phi \frac{v_L - k_1}{\sigma_L} + (1 - p(e^N_u)) \phi \frac{v_H - k_1}{\sigma_H} - e^N_u \}
\end{align*}
\]
Let $\theta$ be the minimum value for which the venture capitalist can still raise a second fund. This random variable $\theta$ is distributed on the interval $(0, 1)$ with cumulative distribution function $F(\theta)$. Therefore, for some given value of $\theta$, the probability of raising a follow-on fund is $F(\theta) = P(\frac{\theta}{\theta} \leq \theta)$.

The expected return of the portfolio is a weighted average of the returns from the status quo private equity portfolio and the additional returns generated from access to top-tier venture capital firms (through both the signaling mechanism and the reciprocity of $LP_H$). Since $\theta_H > \theta_L$, this implies that a skilled limited partner will benefit more from access to these top-tier venture firms than would an unskilled limited partner.

This is for two reasons. The first is that, ceteris paribus, the skilled limited partner’s due diligence abilities exceeds that of the unskilled limited partner. This implies that a skilled limited partner which signaled as such will have the ability to select the best future partners to invest with. Similarly, if an unskilled limited partner successfully signals “skilled,” (which according to the separating model cannot occur), the benefits that accrue will not be as great, since its due diligence process is not as strong.

The model establishes that a portion of the future payoff will be a function of the true skill type of the limited partner, holding signal sent constant. Now the study turns to the returns created from syndication, since this is the driving force behind this chapter’s research.
The payoff generated from syndicated is sourced through two mechanisms, reciprocity from the new syndicate partner \( LP_B \) and the skilled signal which increases access to top-tier venture firms, as discussed previously. As shown, there is a large difference between the top-tier returns and the returns from the rest of the venture capital universe. Thus, it is to the advantage of the limited partner to have access to these funds. Define the probability of participation with these top tier firms by a cumulative distribution function called \( F \).

Formally, define \( \psi_i \) as the lowest value of some random variable \( \psi_i \) where \( i \in (S,U) \) where \( LP_A \) gains access to some of \( LP_B \)'s venture capital funds as a result of reciprocity. \( \psi_i \) is dependent on the true type of the institutional investor \( LP_A \) (skilled or unskilled) and is distributed over the interval (0,1) according to the cumulative distribution function \( F \). Thus for any given value of \( \psi_i \), the probability of access to these venture capital firms is \( F(\psi_i) = \Pr(\psi_i \leq \psi_i) \). This cumulative distribution will be modified by a factor that denotes whether the new fund accessed is high ability or low ability. Denote this factor \( \eta_i \) where \( i \in (L,H) \) and \( \eta_H > \eta_L \).

Now turn to the payoff for signaling. Formally, call the lowest value of \( \phi \) (the limited partner’s probability of being skilled) in which at least one top-tier venture capital firm allows access to one of its future funds as a result of the signal is \( \phi \). This \( \phi \) is a random variable, distributed over the interval (0,1) according to the cumulative distribution
function $F$. Thus for any given value of $\phi$, the probability of access to the top-tier venture firms is $F(\phi) = \Pr(\phi \leq \phi)$

Call $\alpha$ a multiplier which represents the percent difference between the mean top-tier venture capital firm’s expected returns (denoted here $r_T$) and the median return of the rest of venture universe (represented by $r_M$). Finally denote the expected return from the entire venture universe as $\bar{r}$. Thus

$$\alpha = \frac{r_T - r_M}{\bar{r}}$$

is the magnitude that the portfolio’s returns can expect to increase by replacing standard venture capital firms with top-tier venture capital firms.

Denote $u_i$ as the utility generated from the current portfolio, net of access to any new top tier VCs. The model now has the components necessary to construct explicit future expected payoff from signaling as a function of expected utility and the increase in returns generated from exposure to the top-tier VC firms. Call this increase in returns the “selection skill alpha,” or the returns generated from properly selecting, among a set of money managers, the most likely to produce the best results.

Thus for a skilled limited partner who signaled high ability, the expected future payoff, first given as a discounted sum of future expected risk-adjusted returns in Section 2.4.2 can be updated to:

$$w_S^t = \sum_{i=2}^{T} d_i \{ \alpha_{i,S} F(\phi) + \eta_{H,i} F(\psi_{S,i}) \} + u_S$$
It follows for the other cases (skilled, low signal; unskilled, high signal; unskilled, low signal) that the expected future payoffs are as follows:

\[
\begin{align*}
    w^N_S &= \sum_{t=2} d_t [\alpha_{t,S} F(\phi) + \eta_{L,t} F(\psi_{S,t})] + u_S \\
    w^Y_U &= \sum_{t=2} d_t [\alpha_{t,U} F(\phi) + \eta_{U,t} F(\psi_{U,t})] + u_U \\
    w^N_U &= \sum_{t=2} d_t [\alpha_{t,U} F(\phi) + \eta_{L,t} F(\psi_{U,t})] + u_U
\end{align*}
\]

The expected future returns are the products of the returns generated from the management selection ability of the limited partner and the returns generated from exposure to the new venture capital funds resulting from reciprocation by \( LP_B \) and the effectiveness of the “skilled” signal sent to these VC firms.

Thus, it follows that

\[
\begin{align*}
    \Delta_S &= \sum_{t=2} d_t (\eta_{H,t} - \eta_{L,t}) F(\psi_{S,t}) \\
    \Delta_U &= \sum_{t=2} d_t (\eta_{H,t} - \eta_{L,t}) F(\psi_{U,t})
\end{align*}
\]

Since \( u_S > u_U \), Assumption 1 is satisfied.

2.4.4 Future Payoff Conditions for Separation

By Proposition 1, it is known that for some set \( \Delta_U, \Delta_S \), a separating equilibrium exists. If \( \Delta_S \) is large enough relative to \( \Delta_U \), a skilled limited partner will syndicate while the unskilled limited partner will have no incentive to create a syndication. This difference, \( \Delta_S - \Delta_U \), can be decomposed into the following:

\[
\Delta_S - \Delta_U = \sum_{t=2} d_t (\eta_{H,t} - \eta_{L,t}) [F(\Psi_Y) - F(\Psi_N)]
\]
Consider the following proposition:

**Proposition 2** Let \( H = \Delta_s - \Delta_U \). Then the following hold,

1. Holding \( \alpha_U \) constant, \( H \) is increasing in \( \eta_{H,t} \).
2. Holding \( \alpha_S \) constant, \( H \) is decreasing in \( \eta_{L,t} \).
3. Holding \( \alpha \) constant, \( H \) approaches 0 as \( \Psi \) approaches 1.
4. Holding \( \alpha \) constant, \( H \) approaches 0 as \( \Psi \) approaches 0.

Note that as \( H \) increases, so does the potential for a separating equilibrium. The first result of Proposition 2 is straightforward. If the selection skills and the limited partner Value-Add (by way of advice and counsel to the top-tier VC firms) of the skilled limited partner have a greater effect on the returns generated by the top-tier VC firms, then the future payoff to the skilled limited partner is larger and thus the incentive to signal is greater.

The second result also follows intuitively. If manager selection skills and limited partner value-add do not significantly drive the performance of a portfolio of top-tier VC firms then one would expect \( \eta_{U,t} \) to approach \( \eta_{S,t} \) for each time period, which implies a smaller \( H \). This, by extension, implies that there is a greater probability of a pooling equilibrium, as the unskilled limited partners benefit nearly as greatly from access to top-tier VC firms.

The third result of the proposition allows the uncertainty associated with actually acquiring access to these top-tier VC firms to enter into the signaling model. If the top-tier VC firms are certain of the quality of limited partners or if \( LP_B \) will offer nothing in return, then the
model’s separating equilibrium breaks down. A skilled limited partner has no incentive to syndicate to signal if it is fairly certain these top-tier VC’s already know its worth as a partner or if there is no probability of a quid pro quo response by $LP_B$. This suggests that signaling is a game played by relatively “young” limited partners. By young, this means new to the world of private equity investing. Established limited partners, like Princeton, Yale and Harvard have a proven track record of being good, thoughtful partners. Thus, the incentive to syndicate is smaller than compared to limited partners which have proven to be long-term oriented, valuable investors.

Similarly, the fourth result suggests that if the probability of access to the top-tier VC firms is small enough, no signal may be enough to convince these VCs for a spot on the over-subscribed roster. Thus, any signal, $s$, however small, may be too costly if the posterior beliefs do not differ significantly from the prior beliefs.

2.5 Empirical Implications

This model makes predictions on the behavior that appears, at first, counter-intuitive on the part of the limited partners. $LP_A$ invested in a VC fund purposely reduces its pro rata share in a valuable future fund in an effort to bring a fellow skilled limited partner in a syndication of limited partners. The purpose of this action, which strictly reduces $LP_A$ current expected return, is to help gain access using at least two mechanisms to a set of

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24 This is not to suggest that established limited partners do not have other reasons to syndicate (sharing information, quid pro quo, etc.), it is only to suggest that syndication as a signal is most useful for smaller, less-established limited partners.
oversubscribed top-tier VC firms. First, if LP_A gives up some of its shares of a probable high-quality GP to a potential LP_B, it will expect some measure of quid pro quo in return.

Second, it signals its own high quality, which comes in the form of better monitoring of the GPs. These top-tier VCs, which read this signal as credible since it is costly, recognize the value of such partner and may be persuaded to allow access to future funds. Each of these reasons, in turn, increases LP_A future expected returns. The theory behind this model leads to a number of predictions. Here are some of the empirical implications of the model.

**Prediction 1:** Syndication is a decreasing function in limited partner experience levels.

The syndication benefits which accrue to LP_A by way of LP_B, notably additional due diligence on the fund Manager and future joint efforts, will not be as noticeable as the experience of LP_A increases. Said another way, an inexperienced LP_A will benefit from an experienced syndicate partner more than an already experienced limited partner would.

**Prediction 2:** Seeking out syndication is a decreasing function in limited partner familiarity (or notoriety). The venture capital universe, compared to the public market, is small. The general partners who congregate at private equity conferences quickly get to know one another. Thus, the reputation of a limited partner travels quickly within the VC hubs of Palo Alto, Boston and New York out to the rest of the VC world. The need to seek out syndication for signaling purpose alone decreases (though “quid pro quo” remains) as the limited partner becomes more respected and familiar (or infamous) to the universe of
general partners. It is unnecessary to engage in signaling if the LP\textsubscript{A} already has a reputation as a desirable (or undesirable) limited partner.

\textit{Prediction 3:} Holding experience and notoriety constant, limited partners of higher sophistication levels will benefit more from syndication than peers of lower sophistication. This is due to the nature of the outside future payoff. A limited partner with significant investment savvy will be able to recognize and utilize the benefits of access to oversubscribed top-tier VC firms. Limited partners who have fewer investment techniques may not recognize nor take advantage of the opportunities which present themselves when access is finally granted to a top-tier venture capitalist. Conversely, less savvy institutional investors may not properly allocate capital to these assets. This includes under allocation, but, possibly more significant, over allocation. Overzealous investing within private equity to generate large returns could lead to over exposure to the idiosyncratic risk of both the venture capitalist and its portfolio companies.

\textit{Prediction 4:} Syndicated VC funds will have higher expected returns than equivalent funds with solitary investors. Even though the effort put forth by LP\textsubscript{A} decreases if syndication occurs, the model predicts that overall effort, and, ceteris paribus, expected returns will increase. This prediction relies on the concavity of the effort functions of LP\textsubscript{A} and LP\textsubscript{B}. At lower effort levels, their marginal returns from effort are higher. Assuming LP\textsubscript{B} is at least as skilled as LP\textsubscript{A} (which LP\textsubscript{A} believes when selecting LP\textsubscript{B} to join in the syndication), then the sum of the two concave effort functions should be greater than the effort put forth by an unsyndicated limited partner. Therefore, the expected returns from a
VC with syndicated limited partners should exceed the returns of a VC with a solitary investor.

The model limits to one additional limited partner, LP$_B$; which acts as the syndicate partner. The addition of further partners into a syndicate may prove valuable to the original limited partner, LPA, increasing the probability that top-tier VCs allow access to their future funds.

In addition, further research on the shape and amplitude of the limited partner effort functions could prove useful to determine whether or not further syndication is useful. A survey of the literature yields little in the way of empirical results on the effects of limited partner’s efforts to aid their money managers. This model suggests a number of new empirical studies that would be useful.

2.6 Conclusion

Under a set of conditions, the model establishes the existence of a separating equilibrium in which the limited partner syndicates with another limited partner to increase expected future gains. The increase in expected future gains results from an in kind response of access to some of the syndicate partner’s choice funds as well as a credible signal to outside top-tier venture capital firms as to the quality of the signaling limited partner. The signal comes in the form of syndication, in which a limited partner knowingly foregoes part of its pro rata share of a follow-on fund of a VC firm it believes is successful. The LP offers this share to a second skilled limited partner in the hopes of forming a syndicate.
Syndication will surely lower the current expected return of the original limited partner’s portfolio since it has reduced its exposure to a high-ability VC. Syndication will also reduce the optimal effort put forth by the limited partner in its role of partner to the venture capitalist and therefore further reduce expected returns of the current portfolio. These results imply that the signal of syndication is costly (and therefore credible).

The benefit of such a costly behavior is the increased probability of investing in formerly inaccessible (or oversubscribed) venture capitalists. The VCs that are inaccessible are defined as “top-tier” venture capitalists and they control funds that are oversubscribed. The difference between these top-tier VCs’ returns and the returns of the rest of the VC universe are significant and material, thus the occurrence of oversubscription.

The study shows the conditions necessary for syndication rest in the form of a difference in difference equation. The universe of limited partners is divided into skilled and unskilled. If the difference between the expected gain in future payoffs (from access to top-tier VCs) and the losses in current payoffs (from syndication) for skilled limited partners exceeds the identical difference for unskilled limited partners, then conditions for a separating equilibrium exist.

The Cho-Kreps Intuitive Criterion implies that the optimal level of syndication should be the smallest share of the high ability VC’s follow on fund such that a pooling equilibrium does not occur. This makes intuitive sense, as the limited partner considering the signal will wish to do so with the least amount of current payoff lost such that future increases can
be realized. The model assumes that future payoffs are not a function of the signal sent today, therefore the minimum will be sufficient.

The model also derives the function for the expected increase in future payoffs. It was discovered that the expected returns in the future are driven by two factors. The first is the magnitude of the increase in expected value from having the ability to invest in these top-tier VC firms—the limited partner’s skill in picking the high-ability venture capitalists. The second is the probability of gaining access to future top-tier VCs funds.

The signaling game predicts a number of results that can be empirically tested. It states that signaling is more valuable to inexperienced, unknown limited partners. As experience and notoriety increase, the incentives to signal decreases. It also suggests that for any given experience level, a skilled limited partner will benefit more greatly to exposure to top-tier Venture Firms than would an unskilled limited partner. Finally, due to the concavity of the effort functions, the sum of two syndicated limited partners’ effort should produce better expected results for the VC’s follow on fund than the efforts of an unsyndicated limited partner, even though effort is decreasing in syndication.
Appendix: Proof of Results in the text.

Assumption 3: \( \theta_H > \theta_L \)

Proof by equivalence:

1. \( \theta_H > \theta_L \iff \)

\[
2. \frac{P(H|S)Pr(S)}{P(H|S)Pr(S) + P(H|U)Pr(U)} > \frac{P(L|S)Pr(S)}{P(L|S)Pr(S) + P(L|U)Pr(U)} \iff
\]

\[
3. \frac{p_s \theta}{p_s \theta + p_u (1-\theta)} > \frac{(1-p_s) \theta}{(1-p_s) \theta + (1-p_u)(1-\theta)} \iff
\]

4. \( p_s \theta[(1-p_s) \theta + (1-p_u)(1-\theta)] > (1-p_s) \theta [p_s \theta + p_u (1-\theta)] \iff \)

5. \( p_s \theta(1-p_s) \theta + p_s \theta(1-p_u)(1-\theta) > (1-p_s) \theta p_s \theta + (1-p_s) \theta p_u (1-\theta) \iff \)

6. \( p_s \theta(1-p_u)(1-\theta) > (1-p_s) \theta p_u (1-\theta) \iff \)

7. \( p_s (1-p_u) > (1-p_s) p_u \iff \)

8. By Assumption 2, \( p_s > p_u \) which also implies \( 1-p_u > 1-p_s \)

9. \( \therefore p_s (1-p_u) > (1-p_s) p_u \quad QED \)
Derivation of Limited Partner A’s Utility Function

To derive the Limited Partner’s utility function, recall that $e$ will be the effort put forth by the limited partner with respect to the venture capitalist. Effort can be advice and counsel provided to the general partner regarding its portfolio of entrepreneurs. It can be quantified empirically by time spent in contact with the general partners and by the limited partners serving on the Board of some of the general partners’ portfolio companies.

Also, $p(e_i) = \text{Probability of a successful VC fund given the effort level } e \text{ and LP type } i$. Through advice, an informed second opinion and a “steady-hand” investment strategy, the LP can help increase the fund’s success. This increase in the limited partner’s effort is with decreasing marginal productivity. Likewise, the LP cost (time and effort invested come at a cost of other projects neglected) is a function of effort, $e$, and is denoted $c$.

Let $\gamma = \text{the percent of profits secured by the GP, known as the performance fee.}$ Here the variable has range of $0 < \gamma < 1$. Finally, let $\sigma_j$ equal the standard deviation of the institutional investors overall portfolio. Institutional investors will presumably hold well-diversified portfolios across multiple asset classes. Their utility is therefore a function of risk-adjusted returns (typically calculated using the Sharpe ratio) rather than returns alone.
Finally, let $\Phi = 1 - \gamma$. The utility function for all potential outcomes is:

$$U_{LPA} = \begin{cases} 
(1-\gamma)[p(e_i)\frac{(v_j-k_i)}{\sigma_j}] - c(e) & \text{for } i \in [U, S], j \in [H, L] \\
(1-\gamma)(1-p(e_i))\frac{(-k_i)}{\sigma_j} - c(e) & \text{for } i \in [U, S], j \in [H, L] 
\end{cases}$$

It is reasonable to assume that the cost of effort affects skilled and unskilled investors similarly. Therefore, for simplicity in the derivations, normalize the cost function such that $c(e) = e$. This simplifying assumption maintains the first and second order conditions of the cost function.

$$U_{LPA} = \begin{cases} 
(1-\gamma)[p(e_i)\frac{(v_j-k_i)}{\sigma_j}] - e & \text{for } i \in [U, S], j \in [H, L] \\
(1-\gamma)(1-p(e_i))\frac{(-k_i)}{\sigma_j} - e & \text{for } i \in [U, S], j \in [H, L] 
\end{cases}$$

The utility function is only useful for the syndication model if Fund I is going to be a success. In the case of failure, no separating equilibrium can occur, since an LP cannot attempt to signal “skilled” if the signal is based on a failed investment. Thus, the utility function can be further simplified:

$$U_{LPA} = (1-\gamma)p(e_i)\frac{(v_j-k_i)}{\sigma_j} - e \text{ for } i \in [U, S], j \in [H, L], \text{ contingent on fund success}$$
The risk adjusted term, \( \frac{(v_j - k_i)}{\sigma_j} \), hosts multiple variables contingent on the quality of the venture firm as well as the constant cost of investing term. To simplify, let \( \Gamma_j = \frac{(v_j - k_i)}{\sigma_j} \).

For further simplicity let \( \Phi = 1 - \gamma \), which shows the percentage of the profits which flows back to the LP. Thus,

\[
U_{LPA} = \Phi[p(e_i)\Gamma_j] - e \text{ for } i \in [U, S], j \in [H, L], \text{ contingent on fund success}
\]

This utility function \( U \) is in risk-adjusted returns and expresses the expected difference in the LPs overall utility as a result of committing some portion of its overall fund to the GP’s Fund I.
Lemma I: If syndication is feasible, then it strictly reduces the LP’s optimal effort.

Proof by equivalence:
1. $e_i^N > e_i^Y$ for $i \in [U, S] \iff$
2. $p'(e_i^N) < p'(e_i^Y)$, since $p'(e)$ decreases in $e \iff$
3. $\frac{\sigma_i}{\phi(v_i - k_i)} < \frac{\sigma_i}{\phi((1 - s)(v_i - k_i))}$, from FOC $\iff$
4. $(1 - s)(v_i - k_i) < v_i - k_i \iff$
5. $-s(v_i - k_i) < 0 \iff$
6. $v_i - k_i > 0 \iff$
7. $v_i > k_i > 0$, which holds by Assumption 1. QED.
Lemma II: Regardless of syndication level, Skilled LPs exert more effort than Unskilled LPs.
Proof: Desired Results: \( e^l_S > e^l_U \) for \( j \in [Y, N] \)

Case 1: \( i = S \)
Proof by Equivalence:
1. \( e^S_S > e^S_U \) (desired result) \( \iff \)
2. \( p'(e^S_S) < p'(e^S_U) \), by the concavity of the success function \( \iff \)
3. \( \frac{\sigma_H}{\phi[(1-s)(v_H-k_i)]} < \frac{\sigma_L}{\phi[(1-s)(v_L-k_i)]} \), from FOC \( \iff \)
4. \( \frac{\phi[(1-s)(v_L-k_i)]}{\sigma_L} < \frac{\phi[(1-s)(v_H-k_i)]}{\sigma_H} \)
5. \( \Gamma_L < \Gamma_H \) \( \iff \) which is true by Assumption 1. QED.

Case 2: \( i = U \)
Proof by Equivalence:
1. \( e^S_S > e^S_U \) (desired result) \( \iff \)
2. \( p'(e^S_S) < p'(e^S_U) \), by the concavity of the success function \( \iff \)
3. \( \frac{\sigma_H}{\phi(v_H-k_i)} < \frac{\sigma_L}{\phi(v_L-k_i)} \), from FOC \( \iff \)
4. \( \frac{v_L-k_i}{\sigma_L} < \frac{v_H-k_i}{\sigma_H} \)
5. \( \Gamma_L < \Gamma_H \), which is true by Assumption 1. QED.
**Lemma III** : The syndication cost function, $\Lambda_i(s)$, is increasing and concave in $s$.

Proof: First, show that $\Lambda_S$ is increasing in $s$:

1. Recall: $\Lambda_i(s) = p(e_i^y)\phi(\Gamma_L) - e_i^y - [p(e_i^y)\phi((1-s)\Gamma_H) - e_i^y]$ for $i \in [S,U]$

2. $\frac{\partial \Lambda_S(s)}{\partial s} = -p(e_s^y)\phi(-\Gamma_L) - p'(e_s^y)\phi((1-s)\Gamma_H)\frac{\partial e_s^y}{\partial s} + \frac{\partial e_s^y}{\partial s}$

3. $= p(e_s^y)\phi\Gamma_H - \frac{1}{\phi((1-s)\Gamma_H)}\phi((1-s)\Gamma_H)\frac{\partial e_s^y}{\partial s} + \frac{\partial e_s^y}{\partial s}$, FOC

4. $= p(e_s^y)\phi\Gamma_H$, $p(*)$ and $\phi$ are prob. functions and $\Gamma_H > 0$ by Assumption 1

5. $\therefore \frac{\partial \Lambda_S(s)}{\partial s} \geq 0, \forall$ feasible $s$.

Second, show that $\frac{\partial^2 \Lambda_S(s)}{\partial s^2} < 0$

1. $\frac{\partial (\frac{\partial \Lambda_S(s)}{\partial s})}{\partial s} = \frac{\partial p(e_s^y)\phi\Gamma_H}{\partial s}$

2. $= p'(e_s^y)\phi\Gamma_H \frac{\partial e_s^y}{\partial s}$

3. $\frac{\partial^2 \Lambda_S(s)}{\partial s^2} < 0$; since $p'(e_s^y) > 0$ by FOC and $\frac{\partial e_s^y}{\partial s} < 0$ by Lemma 1.
Lemma III: con’t

Third, show that $\Lambda_s$ is increasing in s:

1. \[
\frac{\partial \Lambda_u(s)}{\partial s} = -p(e_u^\gamma)\phi(-\Gamma_u^\dagger) - p'(e_u^\gamma)\phi(1-s)\Gamma_u^\dagger \left\{ \frac{\partial e_u^\gamma}{\partial s} + \frac{\partial e_u^\gamma}{\partial s} \right\}
\]

2. \[= p(e_u^\gamma)\phi\Gamma_u^\dagger, \quad \text{p}(\ast) \text{ and } \phi \text{ are prob. functions and } \Gamma_u^\dagger > 0 \text{ by Assumption 1}\]

3. \[\ldots \frac{\partial \Lambda_u(s)}{\partial s} \geq 0, \forall \text{ feasible } s.
\]

Finally, show that \[\frac{\partial^2 \Lambda_u(s)}{\partial s^2} < 0\]

1. \[\frac{\partial}{\partial s} \left( \frac{\partial \Lambda_u(s)}{\partial s} \right) = \frac{\partial p(e_u^\gamma)\phi\Gamma_u^\dagger}{\partial s}
\]

2. \[= p'(e_u^\gamma)\phi\Gamma_u^\dagger \frac{\partial e_u^\gamma}{\partial s} < 0; \text{ since } p'(e_u^\gamma) > 0 \text{ (FOC)}, \frac{\partial e_u^\gamma}{\partial s} < 0 \text{ (Lemma 1)}.\]
**Lemma IV:** For the syndication cost function $\Lambda$, the following is true:

1. $\frac{\partial \Lambda_S(s)}{\partial s} > \frac{\partial \Lambda_U(s)}{\partial s}$

   and

2. $\Lambda_U(s) > \Lambda_U(s)$ for all feasible values of $s$

**Proof:**

First, show that $\Lambda_H$ is steeper than $\Lambda_L$ for all feasible signals.

Recall that $\frac{\partial \Lambda_i(s)}{\partial s} = p(e^T_i)\phi\Gamma_i$

1. From Lemma 2, we know that $e^T_i > e^T_j$ for $j \in [Y, N]$ and $\forall$ feasible $s$.
2. From Assumption 1, we know that $\Gamma_H > \Gamma_L$.
3. $p(*)$ is increasing in $e$, $\Rightarrow p(e^T_i)\Gamma_H > p(e^T_i)\Gamma_H$
4. $\frac{\partial \Lambda_S(s)}{\partial s} > \frac{\partial \Lambda_U(s)}{\partial s}$

Next, show the magnitude of loss for the skilled LP is greater than the magnitude of loss for the unskilled LP for any feasible signal.

1. $\frac{\partial \Lambda_S(s)}{\partial s} > \frac{\partial \Lambda_U(s)}{\partial s} > 0$ for all feasible $s$, Lemma 3 and above.
2. If we can show that it requires a smaller signal to cause the skilled LP's loss function to equal zero then $\Lambda_S(s) > \Lambda_U(s)$ for all $s$.
3. Recall: $\Lambda_i(s) = p(e^T_i)\phi\Gamma_i - e^T_i - [p(e^T_i)\phi((1-s)\Gamma_H)] - e^T_i$ for $i \in [S, U]$
4. Consider the case of no signal, $s = 0$, here, the loss functions collapse to $\Lambda_i(s) = 0$ for $i \in [S, U]$.
5. Thus $\Lambda_S(0) = \Lambda_U(0)$
6. $\therefore \Lambda_S(s) > \Lambda_U(s)$ for all feasible $s$. 

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**Proposition 1** A separating equilibrium with a unique solution in which only a skilled limited partner syndicates its investments in a high-ability VC exists if the following two conditions hold for the feasible set of $s \in (s_{\min}, s_{\max})$:

1. $s_L \geq s_{\min}$ and $\Delta_s \geq \Delta_s(s_L)$ or $s_L < s_{\min}$ and $s_H > s_{\min}$
2. $\Delta_U < \Lambda_U(s_{\max})$;

This implies one of two unique solutions:

3. If $s_L > s_{\min}$, the unique separating equilibrium is $s = s_L$. This fulfills the Cho-Kreps Intuitive Criterion, with a consequent belief system that $\theta(H) = 1$ if and only if $s \geq s_L$.
4. If $s_L \leq s_{\min}$, then the unique equilibrium is $s = s_{\min}$. This fulfills the Cho-Kreps Intuitive Criterion, with a consequent belief system that $\theta(H) = 1$ if and only if $s \geq s_{\min}$.

**Proof:**

The first condition establishes the circumstances that must exist for a skilled limited partner to be induced to syndicate. In the first case, $s_L$ is at least as large as $s_{\min}$ and the expected future increase for the skilled limited partner exceeds the current loss. This follows directly from Definition 1. In the second part of the first condition, $s_L$ is greater than $s_{\min}$, but there is at least one signal, $s_H$ which provides a small enough loss of current payoff to justify the gain in future payoff. Violating this condition provides no incentive for the skilled limited partner to syndicate its investment.
The second condition keeps unskilled limited partners from pooling with the skilled limited partners. It states that all signals less than or equal to $s_{\text{max}}$ must produce a future expected increase in returns that falls short of the current payoff loss. This also follows directly from the definition of a separating equilibrium. A violation of this implies that the unskilled limited partner would have an incentive to replicate the actions of a skilled limited partner and syndicate its investments.

The Cho-Kreps intuitive criterion will be used to establish the uniqueness of both the “corner” solution ($s_{\text{min}}$) and the interior solution ($s_{L}$). First, let $s_{M} > s_{L}$ be an equilibrium where the unskilled limited partner chooses not to pool through syndication. This follows, since $s_{L}$ is the maximum signal size where the unskilled limited partner suffers no total loss to its portfolio.

Now consider the behavior of the skilled limited partner. The skilled limited partner desires to minimize its losses to the current payoff by minimizing its signal. Its decision to deviate from $s_{M}$ follows since the decision to signal is independent of the actions of other limited partners. Since top-tier VCs still view any nonzero signal as credible, the skilled limited partner will deviate from $s_{M}$ until it reaches $s_{L}$. The skilled limited partner will not deviate from $s_{L}$, as doing so will transform the separating equilibrium to a pooling equilibrium. Therefore, according to the Cho-Kreps intuitive criterion, $s_{M}$ fails the requirements when $(s_{L}, s_{M})$ is non-empty.
Abstract
This paper examines the performance of initial public offerings that were originally financed by venture capital. Venture capital enhances the performance of initial public offerings if the venture capital firm is a specialist within the initial public offering’s industry. Survival rates and performance are higher among specialists as opposed to venture capital firms which invest across multiple industries. Other characteristics observed in this study did not enhance performance. Specifically, venture capital firms which do not just focus on a single stage of development (e.g., seed capital only or early stage only) do not seem to enhance the survival rate of their IPO offspring. The results also support the hypothesis that underwriter prestige improves the survival and performance of initial public offerings. This study benefits from data, specifically the Capital IQ venture capital dataset, which due to difficulty with formatting and structure, has not been used in other studies.

3.1 Introduction
Venture capital firms invest in their portfolio startup companies over a finite time span, always with an eye towards an eventual exit. Exit here is defined as the divesture of the venture capitalist’s interest in its portfolio companies. Venture capital exits can come in one of three basic varieties. If the startup fails or fails to generate value it may be written-off, with all capital invested lost. The startup may be acquired by another firm, usually generating returns of 1 to 2 times capital invested. Typically the best exit, both in terms of capital returned and interest generated, is the initial public offering. A single initial public offering in a venture capital fund can provide returns large enough to drive the overall performance of that fund and encourage capital commitments to future funds. For example, Google generated enormous returns for VC firm Sequoia Partners and all but ensured that Sequoia’s future funds would be fully-capitalized. More recently, Facebook’s anticipated public offering took an ailing Accel Management Co. and placed it on top of the venture capital industry as of mid-2011.

In fact, one way to judge the quality of the venture capital (VC) firm is by the success of its progeny, especially the initial public offerings. Success here shows that these venture capitalists recognize and commit capital to firms deemed worthwhile by underwriters and investors alike. This study investigates how venture capital backed IPOs perform relative to non-venture backed IPOs. It then focuses in on the venture capital characteristics and determines which, if any, have effects on the long-run survival rates and performance of the initial public offerings.
Investors, when faced with the possibility of committing capital to a new issue, will benefit if their due diligence can track the origins of the IPO to a venture capitalist with desirable characteristics. The characteristics must be easily verifiable, as venture capital firms are not regulated like publicly traded funds to disclose financials. Thus, the study will focus on two characteristics which can be known simply by visiting the website of the venture capitalists—(1) does the venture capitalist focus in one industry only (and is therefore considered a “specialist”) and (2) does the venture capitalist commit capital across stages of development or does the firm commit during specific stages only.

The link between IPO performance and VC characteristics can be a useful tool in the toolbox of not only public equity investors, but institutional investors which may commit (and lock up) capital to venture capital firms. In addition to their own qualitative due diligence, some of the only industry data these potential investors (known as limited partners) can rely on when deciding to invest are the performance reports which venture capitalists report to agencies such as Thompson Venture Xpert, VentureOne, Cambridge Associates and Capital IQ.

The voluntary nature of this reporting (they are not like SEC-regulated mutual funds) imply some measure of reporting bias, be it selection or survival bias. For example, Cochran (2005) corrects for selection bias in the VentureOne database. He shows that the mean
arithmetic returns drop from 698% to 59% in that database\textsuperscript{25}. Kaplan et al. (2002) provide evidence contrary to VentureOne claims of no survival bias. They use hand-collected data from 143 willing VC financings (provided by the VC firms themselves) and they show as much as 15% of the rounds were absent from the VentureOne database. The VC firms are more likely to report the rounds if their portfolio companies go public. The existence of such biases makes any comparison of the performance numbers that a potential venture capital investment database provides against industry performance highly suspect.

This study eases information asymmetry between investors in the venture firms themselves by providing the limited partner diagnostic tools that use not the performance of the venture capital fund itself, but the performance of a subset of its exits, the initial public offerings. The data available on publicly traded equity and the performance of initial public offerings are rich with scores of studies which observe various effects on IPO performance. The performance of these IPOs is then matched back to a series of venture capital characteristics. The diagnostic tools rely on readily available and transparent venture capital characteristics, such as if the venture capital firm specializes in one particular industry or invests across industries.

Finally, understanding which VC characteristics produce stronger IPOs directly benefits entrepreneurs seeking out venture capital. Studies show (for example, see Florin [2001])

\textsuperscript{25} These returns do include the late 1990s IPO boom. However, he also reruns the study to exclude anything post 1997 and produces results qualitatively similar results when correcting for selection bias.
the return to entrepreneurs who seek out venture capital is significantly lower than founders who are able to bring their company public without the help of venture money. While this research cannot help these entrepreneurs negotiate better deals with venture capitalists, it can aid them in their VC search process. Using this study, entrepreneurs can seek out venture capital firms with characteristics that will most likely contribute to their IPOs success.

3.1.1 IPO Performance

A study such as this may be rendered less useful if studies showed that initial public offerings consistently outperformed (or at least match) the market in returns and risk-adjusted returns. However, this does not appear to be the case. Motivation for this study stems from the mixed results of studies showing the performance of initial public offerings.

Several studies conclude that initial public offerings underperform the market as measured by various composite indices (e.g., Amex-NYSE Composite). For example, Ritter (1991) demonstrates that IPOs underperform during issuance years of 1975-1984. He nets any effects of underpricing by matching firms’ first day closing prices with their performance after three years. The underperformance of a portfolio of IPOs against a variety of benchmarks (Ritter uses NASDAQ and Amex-NYSE Composite adjustments) worsens as time progresses from the IPO offer date. In addition, he finds underperformance across industries. In fact, every dollar invested in a portfolio of IPOs would net $.83 after three
years of public trading, according to Ritter. He also shows that in years with the highest volume of IPOs (e.g., 1981 and 1983), the underperformance is most severe.

Loughran and Ritter (1995) further lend evidence to IPO underperformance for both IPOs and seasoned equity offerings (new issues from already publicly traded firms, SEOs) during the years of 1970 to 1990. Loughran and Ritter (1995) report five year average returns of 5% annualized and 7% annualized for IPOs and SEOs. Both the IPO and SEO three year performance netted about 80% of wealth relative to a buy and hold strategy of an equal-weighted composite of the NASDAQ and Amex-NYSE. The underperformance worsens as the study shows this ratio drops to about 70% relative to a buy and hold strategy by the fifth year. The source of this data is the Center for Research in Security Prices (CRSP), which will be also employed in my study.

Brav and Gompers (1997) draw different conclusions. Their study, initially based on Loughran and Ritter (1995), focuses on IPOs from 1972 to 1992 for non-Venture Capital backed and 1975 to 1992 for IPOs backed by venture funding. They demonstrate that most of the underperformance comes from smaller, non-venture backed IPOs. They attribute to one of several possibilities including end-point sensitivity (shocks to small growth companies in the 1980s) or the lack of prestigious underwriters among these smaller firms. They conclude that IPOs in the portfolios of institutional investors may not be the hazard once thought.
The uncertainty observed in the literature leads to a few simple tests here. Using the CRSP database, IPOs are matched by cohort year and compared to an equal-weighted composite of the NYSE/NASDAQ and Amex. Table 1 presents the results of this data. For each end point, the average IPO underperforms the Composite Index.\(^{26}\)

\[ S = \frac{E(r) - r_f}{\sigma} \] \hspace{1cm} (1)

where \( E(r) \) is the expected return of the IPO (based on historical monthly returns), \( r_f \) is the historical monthly return of the risk-free asset, the 90 day Treasury Bill and \( \sigma \) is the standard deviation of the historical monthly returns of the IPO.

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\(^{26}\) Note this data excludes any firms which did not (or could not, given a data end date of 12/31/2009) reach twelve months of returns.

\(^{27}\) Annualized cumulative return from issuance to merger, delisting or active trading as of 12/31/2009.
As discussed in a later section, a histogram of IPO lifespans shows that a large number of these firms cease active trading around the three to four year mark. To mitigate survivorship bias (ignoring firms which did not last two years biases the returns of the IPOs upward), this study calculates the two year rolling information ratio. This ratio is long on the portfolio of initial public offerings issued during each month and short an equal-weighted composite of the New York Stock Exchange, the NASDAQ and the American Exchange (rebalanced annually). It is presented in Figure 1.

![Figure 1: Rolling Information Ratio](image)

Care must be taken in the interpretation of Figure 1. First, recognize that the data compare equal-weighted portfolios of IPOs matched to the equal-weighted composite index. Absent rebalancing (transaction) costs, equal-weighted indices tend to outperform value-weighted indices. However, the biases inherent in the use of equal-weighted indices will also apply (and are therefore mitigated to some extent) to the equal portfolio of initial public offerings.

---

28 Where the information ratio is defined as the two year annualized average excess returns over the benchmark (from 1995-2008) divided by the tracking error (the standard deviation of these excess returns).
Given these warnings, the information ratio mirrors the historical context in which it is set. The portfolio of IPOs outperforms the benchmark during the information technology bubble in the late 1990s. After the bubble burst, the information ratio drops below zero, suggesting caution when adding IPOs to an investor’s portfolio. The search now begins for potential characteristics which may mitigate underperformance. One such characteristic, which is the primary focus of this study, is the inclusion of venture capital during the pre-IPO stages of the company’s development.

3.1.2 Venture Capital Backed IPOs

Many IPOs not only underperform but actually cease to be traded in the public market. Studies show a variety of variables which correlate with mitigated underperformance. One such variable might be venture capital (VC) backing. Venture capitalists are professional money managers who help start-up firms expand and grow, providing not only financing (in return for equity) but also operational improvements. Operational improvements include management team building, corporate governance improvement and access to the VC’s networks of suppliers, associates, etc. The ultimate goal of any VC deal is the eventual exit, hopefully through a public offering, which tends to be the most profitable.

Attempts have been made to show the link between the performance of IPOs and venture capital funding. The literature tends to find a positive correlation. Jain (2001) uses a battery of univariate and multivariate logit tests to show that multiple venture capital
characteristics can add to the success of a firm, post-IPO. These characteristics include long-term commitment on the part of the VC, VC-manager strategic fit (which, in some ways will be modeled in this chapter through the variable VC Specialist, discussed in proceeding sections) and early stage involvement (analogous to this study’s VC Early Stage variable, also presented below).

Florin (2003) explores a large variety of venture characteristics and their effects on IPO performance. This study presents effects from the point of view of not only the venture capitalist and the IPO but the entrepreneurial founder. Florin finds that venture backing does improve the size of the IPO and the education and experience of the top management team. Post-IPO long-term performance was not affected by the decision for the founder to seek out venture funding, but venture funding decreases the returns to the IPO’s founder.

The results of Florin (2003) are limited to the year 1996 to eliminate macroeconomic and market effects. Similarly, Jain (2001) uses data from IPOs issued from 1982 to 1990. The data used in this study are from 1995-2009. To compare against the technology driven NASDAQ benchmark, only IPOs which are technology based are included\textsuperscript{29}. The IPOs are sorted into venture and non-venture backed and then are matched to the corresponding NASDAQ decile based on average capitalization size. Table 2 presents the performance results.

\textsuperscript{29} Techamerica.org and OSHA.gov guided the tech versus low-tech/no-tech sorting
For both time spans, venture-backed IPOs outperform their venture backed peers. This result supports Jain (2001). This data span the technology boom and bust as well as the financial crisis of 2007-2009. A simple means test of differences shows that the performance of venture backed IPOs is statistically different from the performance of non-venture backed IPOs by third year of performance. Funds with vintage years (the year in which the individual fund was launched) in the late 1990s were notorious underperformers, yet the effects of venture capital seem to mitigate the underperformance.

The overall performance of the venture backed IPOs relative to non-VC backed IPOs is encouraging. It would be useful to have some better understanding of the effects of venture’s influence, if any, on these performance numbers. Given the nature of private

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30 The average returns will differ from the previous columns, as only months in which there were both non-VC backed IPOs and VC backed IPOs are counted.
equity, the best indicators are ones which cannot, by definition, contain any bias. For example, a venture capitalist can choose whether or not to report the performance of a failed fund. However, that same firm would not hide whether it invested in only one or multiple industry classifications. It benefits a firm in no way to hide this sort of information, as any standard due diligence would reveal such facts. Likewise, it is easily obtained which stage the venture capital fund initially invests in its portfolio companies. These are the characteristics which will be studied here.

The discovery of any linkages between these characteristics and the survival of their IPO progenies will be useful to a broad audience. Investors in venture capital, known as limited partners, will benefit. These limited partners often receive in-kind transfers of IPO shares from venture capital funds as their share of the capital generated by the exit. The limited partner will now have exposure to performance of the IPO in the secondary equity markets. Additionally, investors in initial public offerings will have another set of metrics to help judge the probable success of their investments. Finally, the entrepreneurs themselves will benefit from a better understanding of which venture capital firms produce the more successful initial public offerings.

The database used in this study, Standard & Poor’s Capital IQ, provides details on a number of VC characteristics, notably the industry in which the VCs invest and the stages in which the VCs will invest. The private equity dataset derived in this study has gotten
little use in academic private equity research as of this writing. Thus, the second major contribution of this study is the accumulation of a new dataset.

3.2 The Models

This research uses a time-to-failure hazard model as well as standard performance regressions. Failure is defined as the end of active trading as an independent firm. It can occur either by acquisition by another company (which is not necessarily a bad outcome) or delisting from a major stock exchange (or in one case in the dataset, outright liquidation). These events will be treated separately, though perfect independence is not (and should not) be assumed. The study will focus on a series of VC characteristics. It will test if VC firms which provide capital only in one industry generate IPOs which survive longer and perform better than the IPOs descended from multi-industry VC firms. It will also test if VC firms that fund entrepreneurs earlier tend to produce better results than firms which provide later financing. The study controls for a series of variables including IPO Size, IPO Activity (the size of the IPO market in a given year), Industry success (i.e., the performance of each industry during the year in which the firm goes public), the age of the firm at the time of the offering and the relative prestige of the principle underwriter (typically an investment bank) which backs the firm.

3.2.1 Test Variables

This study primarily focuses on the effects of a set of Venture Capital firm characteristics. These are denoted by the test variables Specialist, Early Stage and Single Stage.
**Hypothesis 1:** IPOs backed by Venture Capitalists which focus narrowly on one industry have a higher survival rate and better returns than IPOs backed by Venture Capital which have no industry focus (so called generalists).

This study will see if there is supporting (or rejecting) of this hypothesis. The study will use the proprietary Capital IQ dataset combined with the Compustat/CRSP variables on the public equity side. The Capital IQ data allows venture capital firms to designate industry(s) of focus. The study designates a “Specialist” as a venture capital firm which focuses on one industry only. A “Generalist” is a venture capital firm which has more than one area of industry focus. Though there is reporting bias inherent in most private equity data, the particular test variable should be unbiased as there is no clear advantage to misrepresenting the firm’s areas of focus.

This hypothesis is motivated from the assumption that knowing an industry well can help a venture firm invest in firms that may have valuable or disruptive technology. Though a venture capital “generalist” may have some industry knowledge, it should not be as extensive as the specialist. Presumably both a specialist venture capital firm and generalist venture capital firm can provide adequate levels of financing and operational support and experience. Thus the addition of industry knowledge is a comparative advantage of these firms.
Hypothesis 2: IPOs backed by Venture Capital firms which invest across stages have a higher survival rate and better returns than IPOs backed by Venture Capital which invests only in the early stages.

This study expands the field of private equity knowledge by supporting (or rejecting) the advantage of early venture capital money against venture capital firms which finance an entrepreneur at any stage. The rationale behind this hypothesis is that a firm which specializes in early stage development can add not only financing but operational improvements at a critical early stage of a company’s development. The Capital IQ dataset also designates stages of investment. In the model, it is assumed that if a venture capital firm confines its initial investments to early stages (so-called Seed, Incubation and Early-Stage) it is considered an early stage investor. Otherwise, all other firms are considered “Other Stage” venture capital firms.

Hypothesis 3: IPOs backed by Venture Capital firms which invest across more than one stage have a higher survival rate and better performance than IPOs backed by Venture Capital which only invest in single stages.

Finally, the study determines if there is an advantage to a venture capital firm which funds initial investments across more than one phase of entrepreneurial development. The firm that invests across multiple stages initially may have a better understanding of the growth and development of the entrepreneurial firm within a larger context (“it sees the forest for
the trees‖). Using the Capital IQ dataset designation of stages of investment, the study assumes that if a venture capital firm confines its initial investments to a single stage only (e.g., the firm only invests at the “Later Stage”), it is considered a “Single Stage” venture capital firm. Otherwise, if the venture capital firm invests initially across two or more stages, it is considered a “Multi-Stage” venture capital firm.

3.2.2 Control Variables

This study focuses on the rate of Venture backed IPOs and its effect on the performance and survival of IPOs. It controls for variables in similar ways to past literature.

*Age of Offering* Several studies have shown the positive link between age of the firm at the time of its IPO and the probability of survival. For example, Ritter (1991) states that age proxies for risk. He shows a positive, monotonic relationship between age and stock performance. The dataset incorporates the Field-Ritter dataset of company founding dates used in Loughran and Ritter (2004) to account for this relationship.

*IPO Size:* Several studies have shown the inverse relationship between IPO size and the risk of failure. Schultz (1993) shows that companies initially offering units (common stock and warrants bundled together) over shares decreases the likelihood of post-IPO survival. Unit offerings are typically associated with smaller IPOs. Hensler et al. (1997) use an accelerated failure time model to show a positive relationship between the size of the IPO
and its survival. Jain and Kini (1999) support this finding by showing that the size of the 
IPO decreases the chances that the public firm will delist or be acquired.

*IPO activity:* Multiple studies show the inverse relationship between IPO performance and 
aggregate IPO volume. For example, Ritter (1991) shows that three-year IPO returns, 
which typically underperform seasoned firms over similar time periods, do even worse 
during years of high IPO volume. Poorly performing IPOs have a higher probability of 
delisting. This result is consistent with the "windows of opportunity" or overvaluation 
hypothesis where low-quality firms are able to go public with reduced probability of 
surviving economic hardship. Additional evidence comes from Lerner (1994). This study 
tracks biotech funding from 1978 to 1992 and discovers that IPO activity is strongly 
correlated with the price public investors are willing to pay. The study contends that IPO 
activity acts as a proxy for additional rounds of VC financing (with commensurate risk).

*Industry Performance:* IPO performance varies by industry over time. Depending on 
endpoints, some industries outperform others. For example, Ritter (1991) shows IPO 
underperformance among most industries during his dataset (1975-1984). In their study of 
IPO survival rates Hensler et al. (1997) discover differing IPO times-to-failure dependent 
on industry.

*Underwriter Prestige:* Several studies connect underwriter prestige with long-run 
performance of IPOs. Broad quantification of underwriter prestige was first developed by
Carter and Manaster (1990) and extended by Loughran and Ritter (2004). The authors use the position of the underwriter on the IPO tombstone (the formal advertisement where the IPO is announced) to proxy for underwriter prestige. These studies show the positive relationship of prestige with IPO performance. This positive relationship allows prestigious underwriters to be selective in choosing firms to IPO.

Carter et al (2004) use the same methodology to show that prestigious underwriters lessen the underperformance of IPOs. They also show that IPOs backed by prestigious underwriters are linked with less underpricing\(^{31}\).

Jain and Kini (1999a) show that monitoring by prestigious underwriters leads to increased IPO success. They attribute this to either superior monitoring skills or ex-ante superior IPO selection abilities. In either case there is a consistent relationship between underwriter prestige and IPO performance.

3.2.3 Performance of Venture-Backed IPOs

The first tests run are simple ordinary least squares test to see if there is support for the three hypotheses. Here the dependent variables are one and three year returns. Table 3 outlines both the variables tested and the control variables, which are discussed in the next section.

\(^{31}\) Underpricing = (First Aftermarket Price - Offer Price)/Offer Price.
Table 3: Model Variables

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Variable Type</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>a1yr</td>
<td>One Year Return</td>
<td>Continuous</td>
</tr>
<tr>
<td>a3yr</td>
<td>Annualized Three Year Return</td>
<td>Continuous</td>
</tr>
<tr>
<td><strong>Test Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>specialist</td>
<td>VC Specialist vs. VC Generalist</td>
<td>Indicator</td>
</tr>
<tr>
<td>earlystage</td>
<td>Early Stage vs. Other-Stage</td>
<td>Indicator</td>
</tr>
<tr>
<td>singlestage</td>
<td>Single Stage vs. Multi-Stage</td>
<td>Indicator</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ageatoffering</td>
<td>Age at Time of Offering in years</td>
<td>Continuous</td>
</tr>
<tr>
<td>transval</td>
<td>IPO Transaction Value</td>
<td>Continuous</td>
</tr>
<tr>
<td>yripoactivity</td>
<td>Yearly IPO Activity</td>
<td>Continuous</td>
</tr>
<tr>
<td>indlyrlag</td>
<td>Lagged One Year Industry Return</td>
<td>Continuous</td>
</tr>
<tr>
<td>uwprst3tier</td>
<td>Underwriter Prestige, Three Tiers</td>
<td>Categorical</td>
</tr>
</tbody>
</table>

3.2.4 Survival Function

The study employs duration model techniques by framing the study within the context of survival analysis. Duration analysis is commonly used in healthcare studies (Berger and Ulm [2003] and Lunn and McNeil [1995]) with failure occurring when a patient dies (or the cancer is cured or other significant events). Duration analysis extends into economics through venues such as unemployment studies (Lancaster [1979]) and hedge fund survival rates (Malkiel et al. [2007]).

In survival analysis, the dependent variable is time until failure. Failure is an irreversible event which removes the subject from further study. For example, in healthcare studies mortality is a common failure event as is morbidity. The study ends, some subjects will not yet experience failure. Those subjects in this category may fail at some point in the future,
Survival analysis focuses not on probability density functions, \( f(t) \) or cumulative density functions \( F(t) = \Pr(T \leq t) \) but on survival and hazard functions. Survival functions focus on the length of time until some event occurs and the subject, in this case, the publicly traded firm, no longer reports. The survival function is defined as:

\[
S(t) = \Pr(T \geq t)
\]  

which is equal to \( 1 - F(t) \). This function shows the probability of surviving beyond time \( t \).

Within the context of this model, survival is continued listing and active trading on a public exchange. The study derives the survival function for the IPOs in the data set below.

The other area of interest is the hazard function \( h(t) \). This function shows the instantaneous rate of failure. Failure is defined as removal from active trading, though this can be for multiple reasons. The IPO survival model fits well under the “competing risks” treatment where not all delisting events are treated the same. Failure can occur from a merger event (the firm is acquired, often at a premium and sometimes at a loss) or a delisting/bankruptcy event (the firm no longer meets the requirements of listing on a public exchange).
The hazard function is the probability that a delisting event (failure) happens during a particular interval, denoted:

\[
h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t + \Delta t > T > t \mid T > t)}{\Delta t} = \frac{f(t)}{S(t)}
\]  

where \( f(t) \) is the probability density function and \( S(t) \) is the aforementioned survival function. The function \( h(t) \) ranges from 0 to \( \infty \), with increasing risk of failure.

Survival analysis can be framed, depending on the nature of the dataset within three general models: nonparametric, semi-parametric and parametric models. Nonparametric models make no assumptions about the shape of the baseline hazard function (the hazard function modeled assuming no treatments or covariates). Semi-parametric models assume that the hazard model is proportional to the baseline hazard model but it leaves the baseline hazard unspecified. One popular way to parameterize the hazard function is as follows:

\[
h(t) = h_0(t) \exp(\beta_0 + x_j \beta_x)
\]

where \( h_0(t) \) is the baseline hazard, \( \beta_0 \) is a column vector of regression coefficients, \( x_j \) is a row vector of multiple predictors and \( t \) is time. In semi-parametric analysis, this is known as the Cox proportional hazard model.

If the underlying baseline hazard function is known or can be estimated, a fully parametric model produces the most efficient results, Cleves et al.(2010). Parametric models can take the form of the proportional hazards (for example, the parametric model with exponential
distribution assumes that the baseline hazard is some constant $c$ and the model collapses to
$h(t) = c \exp(\beta_0 + \textbf{x}_j \beta_j)$. If the model cannot or should not assume proportionality, other
distributions are available. In particular, the baseline hazard function of IPO survival is
probably not constant or monotonic (as the Weibull distribution requires); therefore
parametric models such as the lognormal distribution may provide a better fit.

In fact, even before presenting data, logic supports an inverted U-shape hazard function.
Initially, there is a good deal of excitement surrounding a new public issue, so the
probability of failure is probably fairly small. As time passes, this rate will increase as
excitement dies down and the rigors of meeting quarterly expectations and greater
competition in the public sector hammer away at IPO survival. If a firm can survive these
tests, the probably of a failure event should begin to fall.

To that end, an accelerated failure time (AFT) metric might be (and is, as this data will
show) the appropriate distribution. In particular, the lognormal distribution works well
within the context of one test variable. The lognormal survival function is:

$$S(t_j|\textbf{x}_j) = S_0[\exp(-\textbf{x}_j \beta_j) t_j]$$

(5)

where the baseline survival function is:

$$S_0 = 1 - \Phi \left( \frac{\ln t_j - \beta_0}{\sigma} \right)$$

(6)

where $\Phi()$ is the cumulative distribution function for the standard Gaussian distribution
and $\sigma$ is the standard deviation of the residual of $\ln(t_j)$.
The predictors examined in the parametric and semi-parametric models are presented in Table 4. Within the context of survival analysis, this study focuses on three test variables—Specialist, Early Stage and Single Stage. The control variables are assembled from the literature as variables which have some effect on the hazard rate of IPOs.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Variable Type</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables</strong> (within the context of Survival Analysis)</td>
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<td></td>
</tr>
<tr>
<td>span</td>
<td>IPO Lifespan in months</td>
<td>Continuous</td>
</tr>
<tr>
<td>dlstdcde</td>
<td>Status: Active, Merger Event, Delisting Event</td>
<td>Categorical</td>
</tr>
<tr>
<td><strong>Test Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>specialist</td>
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<td>Indicator</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ageatofferingcent</td>
<td>Centered Age at Time of Offering in years</td>
<td>Continuous</td>
</tr>
<tr>
<td>transvalcent</td>
<td>Centered IPO Transaction Value</td>
<td>Continuous</td>
</tr>
<tr>
<td>yripoactivitycent</td>
<td>Centered Yearly IPO Activity</td>
<td>Continuous</td>
</tr>
<tr>
<td>ind1yrlag</td>
<td>Lagged One Year Industry Return</td>
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<td>uwprst3tier</td>
<td>Underwriter Prestige, Three Tiers</td>
<td>Categorical</td>
</tr>
</tbody>
</table>

3.2.5 Competing Risks

Survival analysis is built on the idea that some event, irreversible, called failure may occur at some point in the future. Once failure occurs, it cannot be undone (e.g., death). Realistically there are often multiple events which can remove a subject from the study.

Cause Specific Hazards

In this dataset, there are several reasons that an IPO may no longer be actively traded. A publicly traded firm may be acquired by another firm (public or private)—a merger event
(CRSP delisting codes in the 200 range). A publicly traded firm may no longer have the characteristics that an exchange needs (e.g., trading volume) to continue listing the company—a delisting event (CRSP delisting codes in the 500 range). A firm may be liquidated—a liquidation event (CRSP delisting codes in the 400 range).

These are fundamentally different events. In a merger, another company seeks out the acquired firm. The final price is usually a premium to the current market price. On the other hand, a delisting event or liquidation event implies that something went very wrong.

See Table 5 for a contrast of the monthly returns for CRSP’s set of IPO mergers and IPO delists.

<table>
<thead>
<tr>
<th>Table 5: Average Final Monthly Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>These are the average final monthly returns among the IPOs which experienced either a merger or were delisted. The data extends from 1/1/1995 to 12/31/2009.</td>
</tr>
<tr>
<td>Merger</td>
</tr>
<tr>
<td>Delisting</td>
</tr>
</tbody>
</table>

Source: CRSP

The difference is clear. Firms which end in delisting on average see a return of -34% in their last month of public trading (dividends included), while firms ending in a merger see the shareholders gaining 1.6% on average leading up to the acquisition. In fact, the underlying data from Table 5 show that about 72% of firms which are no longer actively traded due to a merger have positive returns in their final month of trading. This does not imply that every acquisition is desirable for the acquired company, as an increase in share price might just reflect convergence to the acquisition price.
That said, each of these competing risks implies an entirely different set of circumstances which occurred before “failure” (note that failure here is a technical term, as it was just demonstrated that mergers typically end trading at a premium). Modeling a delisting event study the same as a merger event study would have disastrous consequences. Fortunately, survival analysis\textsuperscript{32} can handle the competing risks models. See Appendix B for details.

This study will examine the interaction of the test variables with each of these competing risks.

3.2.6 Cumulative Incidence Functions

The output produced by the cause specific hazard regressions treats the competing events as censored data. This model produces accurate results only if the competing risks are fundamentally independent. The risk of being acquired is not fundamentally independent from the risk of delisting. There are two sources of correlation. If the firm’s stock price is low, there is a greater risk of both a delisting event and an acquisition (and acquirer takes over the company and fires the current management). On the other hand, if the IPO is doing well, this could represent an increased risk of being acquired (albeit at a premium) while at the same time a decreased risk of being delisted.

To account for this lack of independence from the competing risks, an alternative method for data analysis, the cumulative incidence function, will be employed. The model that is

\textsuperscript{32} And notably the statistical package, Stata 11
used here, developed by Fine and Gray (1999), builds the cumulative incidence function using a semi-parametric analysis. The authors create “subhazard” functions for each of the reasons for failure, defined:

\[
\bar{h}_i(t) = \lim_{\Delta t \to 0} \frac{P[t \leq T < t + \Delta t, \text{ cause } i \text{ failure} \mid T > t \text{ or } (T \leq t \text{ and not cause } i)]}{\Delta t}
\]  

(7)

where \( i \) represents either failure from merger or failure from delisting (and liquidation). For example, function \( \bar{h}_{\text{delisting}}(t) \) is the instantaneous probability of failure due to a delisting event given either no failure up until \( t \) or a merger before \( t \). It does not simply censor the competing risk but allows for the assumption of independence between competing risks to be dropped. This is fortunate as \textit{a priori} there should be an inverse relationship between the likelihood of failure due to a merger (often a healthy firm acquired at a premium) and the likelihood of failure due to delisting (an unhealthy firm which is removed from active trading due a number of unfortunate reasons). The subhazard function for cause \( i \):

\[
\bar{h}_i(t \mid x) = \bar{h}_{i,0}(t) \exp(x\beta_i)
\]

(8)

where \( \bar{h}_{i,0}(t) \) is the baseline subhazard, \( \beta_i \) is a column vector of regression coefficients, \( x \) is the row vector of multiple predictors and \( t \) is time.

The subhazard function will then be used to derive the cumulative incidence function, defined here as:

\[
CIF_i(t) = 1 - \{1 - CIF_{i,0}(t)\}^{\exp(x\beta_i)}
\]

(9)
where \( CIF_{i,0}(t) \) is the baseline cumulative incidence function for each cause \( i \). As long as each cause of failure has a probability greater than zero, the cumulative incidence function for each cause of failure cannot increase to one. This will be graphically presented in the results using a stacked cumulative incidence function.

3.3 Data

Most research in the field of venture capital uses a single source of data, Thompson Venture Economics. This study builds a new dataset using an alternate but equally robust source, Capital IQ (a division of Standard & Poor’s). One of the roadblocks to using Capital IQ is the format of its data. It was designed as an industry tool, not an academic one, so the data are very difficult to work with. The dataset constructed resolves many of these problems and has been successfully transformed into a set that is friendly to statistical programming.

The primary sources of data are the Capital IQ Platform, COMPUSTAT and the Security and Exchange Commission’s (SEC) EDGAR system. The EDGAR (Electronic Data-Gathering, Analysis and Retrieval) system collects from companies all of the forms required by law to be submitted to the SEC. When compiling the characteristic data of the relationship between Venture Capital Firms and their IPO exits, EDGAR provided the final version from the various prospectuses. Every IPO prospectus lists any selling shareholders. This study focuses on 5% owners.
3.3.1 Private Equity Data Source

Extensive searches in both Jstor and Google Scholar reveal that the Capital IQ dataset, while used in other areas of research, has yet to see much use in research on Venture Capital. This may be due to the relative shorter history of private equity data collection compared to other data sources, such as SDC VentureXpert. VentureXpert is considered the most comprehensive data set and has been collecting data on venture capital investments since the mid-1990s.

Capital IQ has been used to study Private Equity excluding Venture Capital. For example, Lerner et al. (2008) use Capital IQ to address whether Leveraged Buyout firms fire managers due to pressures from public shareholders concerned with short-run outcomes. They also test if Leveraged Buyout funds are driven by short-term profit motives at the cost of long-term growth, possibly to boost short-term performance as a response to this shareholder pressure. However, as of this writing, there appears to be little research done using the Venture Capital data collected on Capital IQ.

One of the difficulties in using the Capital IQ dataset is the manner in which data are compiled. Built for industry (not academic) use, the format of the database is not conducive to large sample studies. A summary of the steps necessary to prepare the Capital IQ data is presented in the Appendices.

These characteristics of the venture capital firm are self-reported. Capital IQ compiles the industries in which the venture capitalist invests. Thus, the ex-ante characteristic
“Specialist” will be consistent ex post portfolio composition (unless one of the fund’s portfolio company itself changes its product mid-financing). The stage of financing variable (e.g., Seed/Startup, Early Venture, Mid Venture, Late Venture, Growth Capital) describes the initial stage in which the firm invests. Exits can (and will usually) occur at later stages when the entrepreneur is acquired or commits to an IPO. I added some comments to this effect in the text.

Capital IQ does backfill some of its data, and that is a cause for caution when analyzing fund performance. These performance numbers, however, will be derived from public data available through Compustat and CRSP. The study proceeds with caution anyway, as backfill/survivorship bias will still exist as only successful Venture Capital firms will choose to report their results to Capital IQ. Please see Appendix A for a detailed description of the data collection.

3.3.2 Public Equity Data Source
To establish the links necessary between venture capital and initial public offerings, the study first must establish what percentage of overall IPOs have venture backing. Using a sample of these venture-backed-IPOs, it then will estimate the percentage of control that the venture capitalist firms have on those venture-backed IPOs. The prospectuses of several IPOs, hand-collected from SEC’s EDGAR, provide the necessary calculations.

The characteristics and performance data of the IPOs come from Compustat and CRSP. A product of Standard & Poor’s, Compustat is a database with almost 40 years of
fundamental data for the vast majority of the world marketplace. Compustat stores fundamental attributes and financial statistics. Holding period returns, with dividends included, were drawn from the University of Chicago’s Center for Research Security Prices (CRSP) database. The Compustat/CRSP Merged database allowed me to link the holding period return data to the firm characteristic data.

To examine time to failure, the study includes offer dates and delisting dates from the Compustat/CRSP merged database. The database also provides delisting codes for each IPO. See Table 6 and Appendix B for details. The vast majority of the codes were in the 100s, 200s and 500s.

<table>
<thead>
<tr>
<th>Table 6: CRSP Delisting Codes</th>
</tr>
</thead>
<tbody>
<tr>
<td>100s</td>
</tr>
<tr>
<td>200s</td>
</tr>
<tr>
<td>300s</td>
</tr>
<tr>
<td>400s</td>
</tr>
<tr>
<td>500s</td>
</tr>
</tbody>
</table>

The unique aspect of this dataset is the next step, in which the IPO (and its characteristics and performance) is linked with the Compustat unique identifier, the GVkey\(^{34}\) to its parent VC firm. The final dataset, before filtering for control variables contains 7,313 data points. Multiple venture capitalists backing each IPO account for the increase in data points. This

\(^{33}\) No IPOs in the Capital IQ/CRSP merged database reported “Exchange Changes” and only one company reported a Liquidation event. It was absorbed into the Dropped risk category. See Appendix A for details.

\(^{34}\) Special thanks to Todd Hines, the Assistant Economics and Finance Librarian at Princeton University, who through his efforts, secured the GVkey link to the Capital IQ database. Princeton University, at the time of this dissertation, is the only university to have such a link available to its researchers. The ability to make this connection creates this unique database and made this study possible.
number of observations will decrease when control variables are added. Please see Appendix A for a detailed description of the construction of this data set.

At this point, each row of data contains information on the IPO as well as each venture capitalist which backed it. Data for the venture capitalist include its name as well as test variable indicators (Specialist vs. Generalist, Early Stage vs. Other Stage, Single Stage vs. Multi-Stage). IPO data include the IPO’s lifespan (censored at 12/31/2009), its IPO transaction value, its delisting code, its industry code and an assortment of returns (1 year, annualized 3 year and annualized cumulative returns). Control variables will now be added.

3.3.3 Control Variables Data Sources

Age at Offering: The study controls for the age of the firm at the time of offering from a dataset originally found in Field and Karpoff (2002) and Loughran and Ritter (2004). This dataset, credited to Laura Field and Jay Ritter (hereafter Field-Ritter dataset) contains the founding dates, the first day of trading on CRSP, and the company names for 9,262 U.S. firms which went public. The dataset has been continuously updated with the last addition occurring in January 2011. Ritter and Field only include CRSP-listed IPOs and only if reliable information on the company’s founding data can be obtained. Thus, it is not an exhaustive list of all IPOs. When matching the age of offering to the dataset downloaded from CRSP, approximately 600 observations are lost (out of 3,260 IPOs).
Transaction Value: The model must control for the positive relationship between IPO transaction size and IPO performance. To do this, the study includes an interval variable – the size of the IPO transaction. The source of this data is the Compustat/Capital IQ database.

Size of IPO Activity: To control for the size of IPO activity for each year, the study retains the annualized data on the total size of the IPO activity in a given year. The source of this data is Thomson Financial. The study uses Gross IPO proceeds net of inflation by calendar year. A GNP deflator with base year 1995 accounts for inflation (1995 was chosen as that is the year the dataset begins).

Industry performance: The sample will control for industry performance with a lagged one-year industry return. The use of the lagged return eliminates any look-ahead bias. The Kenneth French Data Library provided the monthly industry performance data. The website’s industry classifications range from 5 industries to 49 industries. Each classification range hosts a number of Standard Industrial Classification (SIC) numbers. For example, the Fama-French industry code “10” (Healthcare, Medical Equipment and Drugs) contains all SIC codes numbering 2830-2839, 3693, 3840-3859 and 8000-8099.

The study uses the 12 industry classification. The 12 Fama-French industries matched up well with the Capital IQ (a division of Standard and Poor’s) Global Industry Classification System (GICS). This is essential in that although the performance and survival data are not
calculated using Capital IQ’ GICS, it is the Capital IQ industry classification system that
develops the “Specialist” test variable. Fortunately, there were few discrepancies between
the Fama-French 12 industry coding and the GICS. The GICS classification
“Discretionary” included the Fama-French codes Consumer Durables, Shops (Wholesale,
Retail and some services) and Other (Entertainment, Hotels, Construction minus Mining
and Transportation). See Table 7 for the comparison.

<table>
<thead>
<tr>
<th>GICS</th>
<th>Fama-French Coding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industrials</td>
<td>Manufacturing + (Transportation/Construction)</td>
</tr>
<tr>
<td>Energy</td>
<td>Energy</td>
</tr>
<tr>
<td>Materials</td>
<td>Chemicals + (Mining)</td>
</tr>
<tr>
<td>Discretionary</td>
<td>Consumer Durables + Shops + (Hotel/Entertain.)</td>
</tr>
<tr>
<td>Staples</td>
<td>Consumer Non-Durables</td>
</tr>
<tr>
<td>Health</td>
<td>Healthcare</td>
</tr>
<tr>
<td>Financials</td>
<td>Finance</td>
</tr>
<tr>
<td>Information Tech.</td>
<td>Business Equipment</td>
</tr>
<tr>
<td>Telecom</td>
<td>Telecom</td>
</tr>
<tr>
<td>Utilities</td>
<td>Utilities</td>
</tr>
</tbody>
</table>

Each classification was matched with an IPO’s corresponding SIC code. Both this
downloaded IPO data and the Fama-French data overwhelmingly use Compustat, not
CRSP, SIC codes. See Table 8 for the IPO count found in each classification from 1995-
2009.\(^{35}\)

\(^{35}\) Out of 2,240 observations, 8 discrepancies were noted and accounted for.
Table 8: 
IPO Count by Industry Grouping
IPO industry count derived from Compustat SIC codes for initial public offerings with venture backing that went public during the years 1995-2009. Source: Kenneth R. French Data Library.

<table>
<thead>
<tr>
<th>Industry</th>
<th>IPO Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer Non-Durables</td>
<td>71</td>
</tr>
<tr>
<td>Consumer Durables</td>
<td>22</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>106</td>
</tr>
<tr>
<td>Energy</td>
<td>72</td>
</tr>
<tr>
<td>Chemicals</td>
<td>22</td>
</tr>
<tr>
<td>Business Equipment</td>
<td>772</td>
</tr>
<tr>
<td>Telecom</td>
<td>109</td>
</tr>
<tr>
<td>Utilities</td>
<td>18</td>
</tr>
<tr>
<td>Shops</td>
<td>201</td>
</tr>
<tr>
<td>Healthcare</td>
<td>260</td>
</tr>
<tr>
<td>Finance</td>
<td>248</td>
</tr>
<tr>
<td>Other</td>
<td>340</td>
</tr>
</tbody>
</table>

The Fama-French data set included monthly returns from each industry. These benchmark data were translated into holding period returns which will match up to the IPO returns generated from CRSP. The study calculates industry 1 year, 3 year annualized and annualized cumulative returns (cumulative based on the lifespan of the IPO).

The returns then act to control for industry performance for each of the test variables in the various models. All of the IPO data had a corresponding SIC code. All SIC codes fell within one of the Fama-French 12 categories. Therefore, no data points were lost with the addition of this control variable.

*Underwriter Prestige:* In Loughran and Ritter (2004), the authors slightly alter and update the ranking system originally developed by Carter and Manaster (1990) which ranks
underwriter prestige. These researchers based their ranking system on the underwriting section of IPOs prospectuses. This section of the prospectus lists the lead investor first followed by non-managing underwriters. A higher placement in the listing indicates higher shares. The more prestigious underwriters will be listed in the top as well. Loughran and Ritter give a top score of 9 to those firms which always appear in the top brackets. The fewer times an underwriter appears in the top brackets, the lower that underwriter’s score. The rankings range from 0-9. These scores are calculated over various time periods and they can vary over time. For example, Alex Brown & Sons was ranked as 9 from 1985-1991 but drops to a rank of 8 during 1992-2000 (Alex Brown & Sons was acquired by Deutsche Bank in 1999).

The study converts the Loughran-Ritter scale into a 3-tier system. A Loughran-Ritter score of 9 translates into “Top-Tier” in this system. Scores of 7 & 8 fall into the “Second-Tier” category. All other scores were considered “Third-Tier.” Of the 1,113 underwriters ranked, only 43, or 3.9%, earned “Top-Tier” status. See Table 9 for details.

<table>
<thead>
<tr>
<th>Table 9</th>
<th>Ranking of Underwriters and Number of IPOs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Column 1 presents the number of underwriters in this dataset as derived from the Loughran-Ritter Dataset of Underwriter Prestige Ranking. Column 2 shows the total number of IPOs generated from each classification of underwriter during the sample period, 1995-2009.</td>
<td></td>
</tr>
<tr>
<td>Number of Underwriters</td>
<td>Number of IPOs</td>
</tr>
<tr>
<td>-------------------------</td>
<td>----------------</td>
</tr>
<tr>
<td>Top-Tier</td>
<td>43</td>
</tr>
<tr>
<td>Second-Tier</td>
<td>180</td>
</tr>
<tr>
<td>Third-Tier</td>
<td>890</td>
</tr>
</tbody>
</table>

Source: Loughran-Ritter Dataset of Underwriter Prestige Ranking and CIQ/Compustat.
Using leads or co-lead underwriters for the IPO dataset, the study matches the Loughran-Ritter underwriter name (and rank) with the Compustat/Capital IQ names\(^{36}\). The number of IPOs backed by “Top-Tier” underwriters is detailed in Table 9. While only 3.9% of the underwriter population, the “Top-Tier” underwriters lead 55% of the IPOs in the 1995-2009 sample set.

When matching the Loughran-Ritter dataset to the CRSP/Compustat data, 269 observations are lost.\(^{37}\) This translates into 5,740 observations in the VC-IPO combined dataset with all control variables accounted for. The increase in numbers results from multiple venture capitalists investing in each IPO. These observations are counted as unique, since the study is a test on the characteristics of each venture capital firm based on the performance of the venture capitalist’s portfolio companies that made it to the public market.

3.4 SUMMARY INFORMATION AND DESCRIPTIVE STATISTICS

3.4.1 The Influence of Venture Capital in the IPO Process

To test the effects of characteristic variables of venture capital firms on IPO survival, the study must first verify that VC ownership (and thus influence) is a significant part of a typical Initial Public Offering. Using the 100 largest IPOs as a proxy for the entire set, the

\(^{36}\) There were considerable discrepancies between the naming conventions used by Compustat vs. the Loughran-Ritter names (for example “J.P. Morgan” vs. “JP Morgan”), but these were matched manually.

\(^{37}\) There were 37 investment banks in the CRSP/Compustat set that were not in the Loughran-Ritter set (these were hand-checked and were not the result of the aforementioned naming convention discrepancies). In addition, 232 observations were lost from Capital IQ transaction identification numbers that did not correspond to the Loughran-Ritter dataset.
study creates an estimate of the percentage of IPOs backed by Venture Capital. The hand-collected prospectuses from EDGAR yielded the following results. Out of the 100 largest IPOs, 11 are venture-backed at the time of the IPO. Of these 11, the average percentage of ownership is 40.6%, dropping to 11.4% post-IPO. The pre-IPO ownership is the point of interest, as the influence of the VC reaches its zenith before the company is publicly traded.

These calculations are supported by larger, more inclusive samples such as Lin and Smith (1998). This study includes 497 IPOs with equity positions provided by 321 VC firms from 1979 to 1990 (with an average of 2.6 VC firms invested in each IPO). Pre-IPO ownership averaged 29.2%, ranging by year from 14% (1984) to 39% (1990). Post-IPO ownership falls to 20.7%.

Cummings (2008) uses proprietary data from a set of European venture capitalists. He shows that from 1995-2002, on average, 40% of VC firms wielded the right to replace a CEO of one of their entrepreneurial firms at any time while 42% held the majority of board seats for their portfolio firms. The median percent of ownership among those portfolio firms which reached an IPO was 55%. In both samples, the share of ownership is significant enough to assume that venture capitalists will influence the organizational structure and direction of the firm as it approaches its initial public offering.
3.4.2 Venture Capital Firm Characteristics

Venture capital summary statistics are presented in Table 10. Approximately 21% of all venture capital firms in this database specialize in one industry only (the so-called “Specialist” indicator variable). For example, Health Enterprise Partners specialize in healthcare entrepreneurs only. Boston-based General Catalyst Partners search across multiple industries when selecting an entrepreneur (though they avoid healthcare and consumer staples, according to both their report to Capital IQ and their firm’s website).

<table>
<thead>
<tr>
<th>Number of VC Firms</th>
<th>Specialist</th>
<th>Generalist</th>
<th>Single Stage</th>
<th>Multi Stage</th>
<th>Early Stage</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>262</td>
<td>1005</td>
<td>268</td>
<td>1085</td>
<td>349</td>
<td>1004</td>
<td></td>
</tr>
<tr>
<td>Average Total IPOs</td>
<td>34</td>
<td>58</td>
<td>25</td>
<td>56</td>
<td>30</td>
<td>57</td>
</tr>
</tbody>
</table>

Table 10: VC Summary Statistics
This table classifies the 1,526 VC Firms in this dataset. To be listed in this set, the VC firm must be a U.S. firm and have at least one IPO exit during the dataset’s time frame of 1995-2009.

<table>
<thead>
<tr>
<th>Multi-Way Sorts</th>
<th>Single Stage</th>
<th>Multi-Stage</th>
<th>Early Stage</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specialist</td>
<td>4%</td>
<td>12%</td>
<td>5%</td>
<td>11%</td>
</tr>
<tr>
<td>Generalist</td>
<td>10%</td>
<td>54%</td>
<td>16%</td>
<td>48%</td>
</tr>
</tbody>
</table>

Source: Capital IQ

38 Please note two items regarding Table 10. First, the number of VC firms will not sum consistently across test variables as some firms did not report their industry or investment stage to Capital IQ. Also, the sample size (5,740 observations) of the data set used to test the model is considerably less than the sum of the number of firms times their average total IPO which can be calculated from this table. The difference results from the loss of observations when the added control variables (e.g., age at the time of offering, underwriter prestige) did not match up exactly with the Capital IQ database or the CRSP IPO database.

39 The percentages for each set of quadrants will not add up to 100% as some firms did not report industry specialization and some did not report any stage of financing.
Firms which only invest in a single stage (one of the early, middle or later stages) comprise about 20% of the sample. Platinum Venture Partners are single stage investors while Siguler Guff & Company provides initial financing during early stage and mid-stage development as well as mezzanine financing. Note that for a firm to be considered “single stage” (as well as early stage) does not preclude the ability to provide follow-on financing (typically at a pro-rata valuation) for their portfolio companies. This just implies that the initial “hunting grounds” for the venture capitalist are confined to a single stage of the entrepreneur’s development.

Firms which focus only on the early stage of the company life cycle (seed/hatch capital, incubation, early-stage) account for about 26% of the Capital IQ sample. Platinum Venture Partners is an example of a firm which is both single stage and early stage. General Catalyst Partners, though primarily an early stage investor, does have a “growth capital” arm which invests later in the firm’s life cycle.

Multi-way sorts are the final rows in Table 10. They show, for example, the percentage of firms that are both “specialists” and “early-stage” investors. Overall, there is not a lot of correlation. Though generalist crossed with either multi-stage or “other” (not early stage) produces the plurality of results (54% and 48%, respectively), this is not surprising—the vast majority of the sample fall into the categories generalists (79%), multi-stage (80%) and non-early stage (74%). The sort results come from the structure of the data rather than systematic variation among the test variables.
As can be seen in Figure 2, the plurality of venture capital specialists is in the field of information technology. This is not surprising given the time the dataset spans (1995-2009). A close second is the venture capital firms which specialize in healthcare. Combined, these two sectors make up 87% of the specialists in this sample data.

![Figure 2: VC Specialists by Industry](image)

This pie chart shows Venture Capital firms which classified as specialist during the period 1995-2009 sorted by the Standard and Poor's GICS coding system. Source: Capital IQ

Telecommunication, utilities and consumer staples were not represented in the sample by any venture capitalists which specialize in those fields. There were many generalist venture capital firms which had invested in these industries (for example Utah Angels invests in both telecommunication and utilities among other industry categories).
The composition of firms which initially invest only in companies at a single stage of development is presented in Figure 3. Slightly more than half of reported single stage venture capitalists invest initially in early stage entrepreneurs (Seed/Incubation/Early stage). About 46% of single stage venture capital firms specialize in later stage (Later Stage/Growth Capital/Mezzanine). Only four firms (1.5%) of those reporting considered themselves mid-stage. Two firms report investments only in PIPEs (Private Investments in Public Equity) firms. See Figure 3 for details.

![Figure 3: Single Stage VCs](image)

This pie chart shows Venture Capital firms which classified as single stage during the period 1995-2009 using the classifications in the Capital IQ database. Source: Capital IQ

3.4.3 IPO Survival Statistics and Summary Performance

Table 11 presents the summary statistics of the venture-backed Initial Public Offerings in the sample. The average time to failure for both a delisting event and a merger event is 47 months (coincidentally as they were calculated separately). The average time to failure for
a firm which survives (remains actively traded) the sample period is not calculated as the
data are simply censored at 12/31/2009.

Table 11 also calculates the average age of the company at the time of its initial public
offering. As expected (See Ritter[1991]) the more successful conclusions—mergers or
survival—correspond to firms which are on average older at the time of public offering,
180 and 240 months, respectively. The age at offering of a firm that delists averages only
about 11 years from founding to public offering.

The size of the initial public offering presented in Table 11 is consistent with other findings
(for example, see Jain and Kini [1999]). The transaction value of the firms which survive
is over 2.5 times as large as firms which fail due to delisting. The average smaller size of
IPOs which end up in a merger could be explained since, ceteris paribus, it is easier to
acquire firms which, in absolute terms, are smaller in size. If you compare the $80 million
average transaction value to the average firm size which survives, the surviving firms IPO
is almost 3 times as large.
A histogram of all initial public offerings in the dataset is derived. The shape of the histogram is of interest. Though failure seems to peak around 3 years, there is an upswing again around 11 years. See Figure 4 for details.

The plotted histogram of just the surviving firms separate from those experiencing failure produces results that explain away the odd-shaped Figure 4. In Figure 5, only those firms which are actively traded are reported. The twin-peaked shape of this histogram is entirely dependent on the start date (January, 1995) and the end date (December 31, 2009).
The bimodal distribution corresponds with both the information technology boom of the late 1990s (120-160 months) as well as strong years for initial public offerings, 2004 to 2007. The technology bust which began in the early part of the 21st century corresponds with the less-filled buckets of 80 to 110 months. The financial crisis of 2007-2009 can be detected in this graph. The 2008-2009 markets were sparse for initial public offerings and there are a low number of venture-backed IPOs.

Once survival is netted out, the IPO lifespan distribution took on a more familiar look. Figure 6 shows that most of the initial public offerings which failed did so around the three to four year mark. Only 6 firms delist by 10 months with the majority of the failures due to mergers which occur shortly after the public offering. Almost 37% of the firms which fail due to delisting do so during the 21st and 40th month of public trading. Similarly, about 33% of the firms which fail due to a merger event do so between the 21st and 40th month.
The distribution of these failure times most closely resembles a lognormal or loglogistic distribution within the context of survival analysis.

Also in Figure 6, the patterned bars to the right of the solid bars show the mergers and delisting events for IPOs which were offered during 1999 and the first four months of 2000. This period, the height of the Tech Boom, had a large number of IPOs (just 16 months, or 9% of the overall time span generates 26% of the IPOs in this sample). The failures, though representing a large portion of the overall data set, do not show a shape or distribution significantly different from the failure pattern of the entire sample.

The data presented in Figure 6 shows perhaps an abnormally large number of merger events relative to delisting events. This runs contrary CRSP data which reports about 1 merger for every 6 delisting events. Once the context of the Capital IQ database is considered, this makes sense. The firms in this dataset are venture backed. Venture funds tend to invest in technology firms. Figure 7 shows classification of the IPOs by the
Fama-French industry classification. Firms based on technology, specifically Healthcare and Business Equipment (The Fama-French classification which includes computers, software, and electronic equipment) tend to be acquired at a higher rate than lower tech firms (the acquirer in effect purchases the research and development of the tech IPO). For example, notice that about 46% of the Business Equipment IPOs are acquired while delisting events dominate the failures in the Consumer Durables and Chemical classifications.

When looking at the failures by industry, Figure 7 charts each event as a percentage of all firms within each industry. This is done for comparability reasons. For example, there are only 16 venture-backed initial public offerings that classify as “utilities” during the time period of 1995-2009; over 80% survive to December 31, 2009. On the contrary, of the 772 “business equipment” only 252, or roughly one-third, of the public companies remain actively traded.
Comparing just delisting events shows some variation among industries. For example, about 40% of venture-backed IPOs within the consumer durables and telecom industries fail from delisting. However, only 15% and 19% respectively, of healthcare and finance venture-backed IPOs failed due to a delisting event.

The summary performance of venture-backed IPOs is described in Table 12. It presents the mean 1\textsuperscript{st} year returns as well as the mean annualized 3 year return and mean annualized cumulative return. The results are sorted into buckets which correspond to the state of the firm at the end of the sample—Survival (actively traded) or Failure (from a delisting event or a merger event). There is a fourth category which calculates the average of all initial public offerings within the sample.

<table>
<thead>
<tr>
<th></th>
<th>Delisting Event</th>
<th>Merger Event</th>
<th>Survival</th>
<th>All IPOs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Year Return</td>
<td>-25.8%</td>
<td>4.5%</td>
<td>14.5%</td>
<td>1.9%</td>
</tr>
<tr>
<td>3 Year Return (Annualized)</td>
<td>-19.2%</td>
<td>-9.3%</td>
<td>-4.4%</td>
<td>-14.4%</td>
</tr>
<tr>
<td>Annualized Cumulative Return</td>
<td>-58.7%</td>
<td>-8.4%</td>
<td>-6.4%</td>
<td>-19.5%</td>
</tr>
</tbody>
</table>

Firms that did not survive the study due to delisting performed the worst, regardless of the time length of performance measured. Firms that were right-censored (survived as of 12/31/2009) earned the highest. IPOs which were merged with other firms performed better than those that failed due to delisting but not as strong as the firms which survived.
Firms that did not last a full year (or full 3 years), either from failure or censoring, were not included in the calculations.

3.4.4 Survival Model Summary Statistics

Once the venture capital firms have been matched with their corresponding initial public offerings and all control variables are added, 5,740 observations remain. Table 13 provides the summary of these variables. Note that each test variable (Specialist, Early Stage and Single Stage) has fewer observations than the entire sample. This is due to several venture capital firms failing to report industry and/or stage focus.

Table 13 has a few points of interest. The average percentage of IPOs which are backed by specialist, early stage and single stage venture capitalists falls when these venture capital firms are matched with their IPO. The specialist percentage drops from 21% to 16%, early stage from 26% to 15% and single stage from 20% to 11%. This decrease indicates that generalist and multistage venture funds seem to have a higher volume of IPOs than those which specialize by industry or stage. This is consistent with the average number of IPOs per group generated by the Capital IQ venture database.
The mean returns for all IPOs in the sample are similar to the results from the IPO database before it was matched to the venture capital database. This lends some measure of confidence to the model. Similarly, age at offering and transaction value are similar in value pre-VC matching and post-VC matching.

---

**Table 13: Variable Summary Statistics**

This table provides the summary statistics for the test variables (e.g., a mean of .16 for VC specialist indicates that 16% of the sample classifies as an industry specialist). The sample set of 5,740 observations ranges from 1995-2009 and merges 1,526 venture capital firms to the 2,241 initial public offerings they backed during this time period. Source: CRSP/Capital IQ Merged

<table>
<thead>
<tr>
<th>Variables</th>
<th>Obs.</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPO Lifespan (years)</td>
<td>5740</td>
<td>5.8</td>
<td>3.4</td>
<td>0.2</td>
<td>13.9</td>
</tr>
<tr>
<td><strong>Test Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VC Specialist (1) vs. Generalist (0)</td>
<td>5219</td>
<td>0.16</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Early Stage (1) vs. Other-Stage (0)</td>
<td>5340</td>
<td>0.15</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Single Stage (1) vs. Multi-Stage (0)</td>
<td>5340</td>
<td>0.11</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age at Time of Offering (years)</td>
<td>5740</td>
<td>10.3</td>
<td>13.1</td>
<td>0.5</td>
<td>149.4</td>
</tr>
<tr>
<td>IPO Transaction Value ($ millions)</td>
<td>5740</td>
<td>197.6</td>
<td>1123.5**</td>
<td>5.6</td>
<td>17864.0</td>
</tr>
<tr>
<td>Yearly IPO Activity ($ billions)</td>
<td>5740</td>
<td>45.3</td>
<td>17.9</td>
<td>10.1</td>
<td>65.1</td>
</tr>
<tr>
<td>Lagged Industry 1 Year Return</td>
<td>5740</td>
<td>29.9%</td>
<td>27.8%</td>
<td>-63.5%</td>
<td>105.0%</td>
</tr>
</tbody>
</table>

---

40 This summary does not include the indicator variable underwriter prestige. This three-tiered indicator does not translate well into a mean/standard deviation summary. Furthermore, the summary statistics for this indicator are presented in the data section.

41 Transaction Value has a few massive outliers which influence the standard deviation (such as the Visa IPO).
3.5 EMPIRICAL RESULTS

The test variables Specialist, Early Stage and Single Stage produced markedly different results. The results for specialist support the hypothesis that a venture capitalist firm which specializes in a particular industry has an improved performance and survival outlook, definitely for survival against delisting. For the earlystage and singlestage, the model (under a battery of tests) found no statistically significant effects by these characteristics to improve the odds of survival. The results strongly reaffirm other studies which show the correlation between the prestige of the underwriter and the IPOs success and survival.

3.5.1 Performance Results

The results of the univariate regressions, using ordinary least squares, specified as \( ret_i = \alpha + \beta_i (x_i) \) for the variables specialist, singlestage and earlystage are presented in Table 14. With no control variables, none of the results were significant at 5%. The signs of the coefficients are consistent with the hypotheses, with the exception of IPO returns backed by VC Specialists after one year.

<table>
<thead>
<tr>
<th></th>
<th>One Year Returns</th>
<th>Annu. 3 Yr. Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Std. Error</td>
</tr>
<tr>
<td>Specialist Venture Capitalist</td>
<td>-.083</td>
<td>.044</td>
</tr>
<tr>
<td>Single Stage Venture Capitalist</td>
<td>-.081</td>
<td>.051</td>
</tr>
<tr>
<td>Early Stage Venture Capitalist</td>
<td>-.086</td>
<td>.045</td>
</tr>
</tbody>
</table>
Adding the control variables described in Table 15 and discussed in Section 3.3.3 keeps most of the test variables insignificant. The basic multivariate specification is as follows:

\[ \text{ret}_i = \alpha + \beta_x(x_i) + \sum_j \beta_j(y_{ij}) \]  

(10)

where \( \text{ret}_i \) is the annualized return (one or three year) of the observation, \( x_i \) is the indicator test variable (Specialist, Early Stage, Single Stage) and each \( y_{ij} \) is the \( j^{th} \) control variable (age at offering, IPO transaction value, yearly IPO returns, industry annualized return and underwriter prestige) for each observation. For brevity, the study presents here only results in which the test variable showed significant results. In this case, only the three year annualized return regression conditional on delisting with test variable Specialist showed statistical significance.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Annualized Three Return, Delisting Event</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td>VC Specialist</td>
<td>.120*</td>
</tr>
<tr>
<td>Age at Offering</td>
<td>.003**</td>
</tr>
<tr>
<td>IPO Transaction Value</td>
<td>.000**</td>
</tr>
<tr>
<td>Yearly IPO Activity</td>
<td>.000**</td>
</tr>
<tr>
<td>Lagged Industry Return</td>
<td>-.212</td>
</tr>
<tr>
<td>Underwriter Prestige: Top Tier</td>
<td>.107</td>
</tr>
<tr>
<td>Underwriter Prestige: 2nd Tier</td>
<td>.083</td>
</tr>
<tr>
<td>Constant</td>
<td>.192</td>
</tr>
</tbody>
</table>

* Significant at 5%; ** Significant at 1%

The results show that a firm backed by a venture capital specialist that eventually ends in a delisting event will have better overall performance compared to a firm backed by a
specialist test variable, annualized three year returns conditional on delisting, merger and actively traded (respectively). Columns 2, 5 and 8 present the standard error and columns 3, 6 and show the significance level. For brevity, the table omits the results other control variables (specialist, age at offering, IPO transaction value, yearly IPO activity, industry return). The data span the years 1995-2009. Source: CRSP/Capital IQ Merged

<table>
<thead>
<tr>
<th></th>
<th>Delisting</th>
<th>Merger</th>
<th>Actively Traded</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>Std. Error</td>
<td>P&gt;</td>
</tr>
<tr>
<td>Top Tier</td>
<td>.107</td>
<td>.057</td>
<td>.06</td>
</tr>
<tr>
<td>2nd Tier</td>
<td>.083</td>
<td>.060</td>
<td>.17</td>
</tr>
</tbody>
</table>

(All Other Variables Omitted)
3.5.2 Survival Analysis, Test Variable: Specialist

As presented in section 3.3, one interesting aspect of IPO survival study is that there are competing risks for failure. Failure can result from a merger, delisting, liquidation or a physical change in exchanges. With only one exception\textsuperscript{42} all observations in the sample either survive (considered right-censored data), experience a merger event (could be bad outcome but could be a good outcome, as often mergers occur at a premium to current price) or delisting event (generally considered a bad outcome).

Nonparametric Analysis and Semi Parametric Analysis

With no functional form, nonparametric analysis is a good place to begin survival analysis. It allows the data to speak for itself, as no underlying assumptions are made about the shape of the hazard function. Nonparametric analysis, also assumes nothing about the distribution of the covariates of the model, but establishes the positive relationship between specialist and survival in the context of the risk of delisting. Semi-parametric analysis generates coefficients for test and control variables. The study uses the Cox proportional hazards regression to explore these coefficients under both cause-specific risks—the risk of a delisting event and the risk of a merger event.

Given the distribution of IPO lifespan, parametric analysis (with lognormal distribution) generates the best fit, as will be demonstrated below. The results of the nonparametric and

\textsuperscript{42} One firm, Highlands Acquisition Corporation liquidated in October, 2009. This data point was folded into the delisting category. It was backed by only one venture capitalist in the dataset.
semi-parametric analyses support the parametric model, so they are omitted here for brevity. The results can be viewed in Appendix B.

Parametric Models

Though semi-parametric analysis is an excellent first step towards describing the effects of the covariates, however the data probably fit better if the assumption of proportional hazards is relaxed. This follows from the shape of the IPO lifespan histograms generated previously. In both competing risk cases, failure rates accelerate as time approaches 40-50 months and then decrease beyond that. An accelerated failure time (AFT) model, within the context of a parametric regression may prove a better fit than the proportional hazards assumed by the Cox regression. This is true for both the baseline hazard function as well as the coefficients of the covariates. Parametric modeling will now be used to estimate the baseline hazard function and the effects of the covariates. The analysis will maintain the assumptions of the competing risk model.

The analysis is limited to distributions that fit within the AFT metric (Exponential, Weibull, Lognormal and Loglogistic). The shape of the distribution seen in Figure 8 resembles an inverted-U which is impossible with both the constant baseline hazard distribution (Exponential) and the monotonic Weibull. One of the variable hazard shaped distributions (Lognormal or Loglogistic) is most likely the best fit.
The Akaike Information Criterion found in Akaike (1974) provides the selection criteria necessary to select the model with the best fit. For parametric survival models,

\[ AIC = -2 \ln L + 2(k + c) \]  

where \( \ln L \) is the log-likelihood function, \( k \) is the number of model covariates and \( c \) is the number of model-specific distributional parameters (e.g., the lognormal, which is not monotonic, has \( c = 2 \) since it has both an intercept term, \( \beta_0 \), and a parameter, \( \sigma \), which describes the shape of the curve). Since the fit of the model is achieved when the log-likelihood is maximized, the smallest value of the AIC will be the model with the best fit. Table 17 shows the Akaike Information Criterion.
Table 17:
Akaike Information Criterion, Specialist Test Variable

Columns 1-2 show the log-likelihood and the results of the Akaike Information Criterion test applied to the hazard analysis of venture-backed IPOs conditional on a merger event. Columns 3-4 show similar results applied to the survivability of venture-backed IPOs conditional on delisting. The data span 1995-2009. Source: CRSP/Capital IQ Merged.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Merger Event</th>
<th>Delisting Event</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log-Likelihood</td>
<td>AIC</td>
</tr>
<tr>
<td>Exponential</td>
<td>-3874</td>
<td>7763</td>
</tr>
<tr>
<td>Weibull</td>
<td>-3727</td>
<td>7472</td>
</tr>
<tr>
<td>Lognormal</td>
<td>-3637</td>
<td>7291</td>
</tr>
<tr>
<td>Logistic</td>
<td>-3699</td>
<td>7415</td>
</tr>
</tbody>
</table>

According to AIC, the distributions with variable hazard shape, lognormal and loglogistic, fit best. Lognormal has the absolute lowest score for both the merger risk case and the delisting case and thus is the choice for the model. The other distributions can be rejected, on a relative basis.

The resulting coefficients in Tables 18 and 19 between the accelerated failure time and proportional hazard (included for reference) models seem markedly different, but once properly interpreted, they tell similar stories. The proportional hazard (Cox) model presents hazard ratios which, when less than 1, imply that the variable decreases the hazard rate. The AFT model calculates time to failure. Any positive covariate coefficients suggest an increase in time to failure (and thus a lower hazard rate). In that light, the results of the parametric model are entirely consistent with the semi-parametric regression.

Table 18 presents the results of the parametric regression for the case of a merger event with specialist treatment. The results are consistent with the Cox regression, which is
displayed to the right of the parametric results. A specialist VC has no statistically significant effect on time to failure.

### Table 18: Hazards Results – Merger Event, Specialist Test Variable

Columns 1-4 show the results of the parametric model with assumed lognormal distribution, conditional on a merger outcome. Columns 5-8 show the results of the Cox proportional hazards regression conditional on a merger event for comparison (See Appendix B for details). The data span the years 1995-2009. Source: CRSP/Capital IQ Merged

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Parametric Model: Lognormal</th>
<th>Semi-Parametric Model (Cox)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(AFT)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Effect on Time to Failure</td>
<td>Hazard Ratio</td>
</tr>
<tr>
<td></td>
<td>Standard Error</td>
<td>Standard Error</td>
</tr>
<tr>
<td></td>
<td>P&gt;</td>
<td>z</td>
</tr>
<tr>
<td>VC Specialist</td>
<td>.043</td>
<td>0.926</td>
</tr>
<tr>
<td></td>
<td>.051</td>
<td>.067</td>
</tr>
<tr>
<td></td>
<td>.40</td>
<td>.29</td>
</tr>
<tr>
<td>Age at Offering</td>
<td>-.004**</td>
<td>1.004</td>
</tr>
<tr>
<td></td>
<td>.001</td>
<td>.002</td>
</tr>
<tr>
<td></td>
<td>.00</td>
<td>.06</td>
</tr>
<tr>
<td>IPO Transaction Value</td>
<td>.000**</td>
<td>0.999**</td>
</tr>
<tr>
<td></td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>.00</td>
<td>.00</td>
</tr>
<tr>
<td>Yearly IPO Activity</td>
<td>.000</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>.83</td>
<td>.93</td>
</tr>
<tr>
<td>Lagged Industry Returns</td>
<td>-.053</td>
<td>1.187**</td>
</tr>
<tr>
<td></td>
<td>.082</td>
<td>.134</td>
</tr>
<tr>
<td></td>
<td>.51</td>
<td>.13</td>
</tr>
<tr>
<td>Underwriter: Top Tier</td>
<td>-.564**</td>
<td>2.610**</td>
</tr>
<tr>
<td></td>
<td>.141</td>
<td>.640</td>
</tr>
<tr>
<td></td>
<td>.00</td>
<td>.00</td>
</tr>
<tr>
<td>Underwriter: 2nd Tier</td>
<td>-.637**</td>
<td>2.941**</td>
</tr>
<tr>
<td></td>
<td>.143</td>
<td>.726</td>
</tr>
<tr>
<td></td>
<td>.00</td>
<td>.00</td>
</tr>
<tr>
<td>Constant</td>
<td>3.059**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>.143</td>
<td></td>
</tr>
<tr>
<td></td>
<td>.00</td>
<td></td>
</tr>
<tr>
<td>Sigma</td>
<td>1.017</td>
<td></td>
</tr>
<tr>
<td></td>
<td>.143</td>
<td></td>
</tr>
<tr>
<td></td>
<td>.00</td>
<td></td>
</tr>
</tbody>
</table>

* Significant at 5%  ** Significant at 1%

In addition, the results of the control variables are consistent with the Cox model. If backed by a prestigious underwriter, a firm’s public life expectancy before a merger is reduced by over 70% (for both tiers). If brought public during a “hot” market (the industry 1 year return is high), then the firm’s time to acquisition is reduced by about 30%. There is a similar effect on survival by the age of the firm at the time of its public offering.

The results for the delisting event risk match up with the Cox model. Table 19 shows that if a venture capital firm specializes in a particular industry, any of its portfolio companies that eventually go public survive (do not delist) about 14% longer than firms backed by
generalist venture capital funds. This lends support to Hypothesis 1, the specialist-backed IPOs will survive longer than generalist-backed IPOs.

The results of the control variables are consistent with the Cox model. This model strengthens the argument that underwriter prestige increase survival rates. If backed by a prestigious underwriter, a firm’s public life expectancy is almost doubled. There is a similar, but smaller effect on survival by the age of the firm at the time of its IPO.

Cumulative Incidence Function

The competing risk model provides a way to show the cumulative incidence of hazard for each event where no assumption of independence between the merger risks and the delisting risks is assumed. This model most closely resembles the semi-parametric model

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Parametric Model: Lognormal (AFT)</th>
<th>Semi-Parametric Model (Cox)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Effect on time to Failure</td>
<td>Standard Error</td>
</tr>
<tr>
<td>VC Specialist</td>
<td>.143*</td>
<td>.068</td>
</tr>
<tr>
<td>Age at Offering</td>
<td>.008**</td>
<td>.003</td>
</tr>
<tr>
<td>IPO Transaction Value</td>
<td>.000**</td>
<td>.000</td>
</tr>
<tr>
<td>Yearly IPO Activity</td>
<td>-.000**</td>
<td>.000</td>
</tr>
<tr>
<td>Lagged Industry Return</td>
<td>.111</td>
<td>.098</td>
</tr>
<tr>
<td>Underwriter: Top Tier</td>
<td>.909**</td>
<td>.114</td>
</tr>
<tr>
<td>Underwriter: 2nd Tier</td>
<td>.942**</td>
<td>.118</td>
</tr>
<tr>
<td>Constant</td>
<td>2.094**</td>
<td>.113</td>
</tr>
<tr>
<td>Sigma</td>
<td>1.145</td>
<td>.028</td>
</tr>
</tbody>
</table>

* Significant at 5%  ** Significant at 1%
using a Cox regression. Table 20 reports the results from Equation (7). Coefficients in this model are known as subhazard ratios and their interpretation is similar to previous hazard ratios. The difference is that the merger events, previously censored, are treated as still at risk (though with different weightings to account for the competing risk).

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Merger Event</th>
<th>Delisting Event</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sub Hazard Ratio</td>
<td>Robust Std.</td>
</tr>
<tr>
<td>VC Specialist</td>
<td>.951</td>
<td>.068</td>
</tr>
<tr>
<td>Age at Offering</td>
<td>1.005*</td>
<td>.002</td>
</tr>
<tr>
<td>IPO Transaction Value</td>
<td>.999**</td>
<td>.000</td>
</tr>
<tr>
<td>Yearly IPO Activity</td>
<td>1.000</td>
<td>.000</td>
</tr>
<tr>
<td>Lagged Industry Return</td>
<td>1.153</td>
<td>.131</td>
</tr>
<tr>
<td>Top Tier Underwriter</td>
<td>3.300**</td>
<td>.827</td>
</tr>
<tr>
<td>2nd Tier Underwriter</td>
<td>3.647**</td>
<td>.920</td>
</tr>
</tbody>
</table>

* Significant at 5%  ** Significant at 1%

The results are entirely consistent with previous regressions. The test variable behaves similarly to both the standard Cox proportional test and the parametric regressions with lognormal distribution. Relaxing the assumption of independence between the competing risks reduces the significance of specialist for both event risks. Though the signs remain the same, specialist’s P-value slightly increases to .05% for the delisting event, still significance at 5%. The result for the merger case remains statistically insignificant.

One result of note is that the relaxation of the independence assumption causes the effect of underwriter prestige to come into sharper focus. Underwriter prestige encourages merger
events and discourages delisting events. A firm backed by either a top-tier or second-tier underwriter has triple the hazard rate of a merger event than a firm which is not. Furthermore, the backing of a prestigious underwriter cuts the hazard rate of delisting by over 70%.

Figure 9 shows the cumulative incidence function of the treatment group (VC Specialist) versus the control group (VC Generalist). Here the event of interest is the delisting event; VC specialist reduces the incidence of that event.

With the relaxation of the assumption of event independence, it would be nice to see how the risks of each event differed from VC Generalist to VC Specialist. Figure 10 shows the stacked cumulative incidence plots where all covariates except specialist are ignored. The
graphical depiction\textsuperscript{43} of the results verify the conclusions—a venture capital specialist will help keep an IPO from delisting but probably has no effect on the risk that an IPO will be acquired.

3.5.3 Survival Analysis, Test Variable: Early Stage

This section establishes that the relationship between Early Stage and IPO survival is much weaker. The effects are not statistically significant. Some of the regressions produce

\textsuperscript{43} The Stacked Cumulative Incidences look remarkably similar for the control and treatment groups. However, the area for the delisting event is larger for the generalist plot compared to the specialist plot. For verification, note the identical positioning of the label “Delisting Event” across both plots.
coefficients that are the opposite sign than predicted by the hypothesis. For brevity, the nonparametric and semi-parametric results are located in Appendix C.

Parametric Model

Parametric analysis will be used to increase model efficiency and reject with more confidence Hypothesis 2. Recall that the shape of the lifespan of initial public offerings is neither constant nor monotonic so only accelerated failure time metrics will be considered. Table 21 generates the values of the Akaike Information Criterion for each of the competing risk events.

Table 21: Akaike Information Criterion, Early Stage Test Variable
Columns 1-2 show the log-likelihood and the results of the Akaike Information Criterion test applied to the hazard analysis of venture-backed IPOs conditional on a merger event. Columns 3-4 show similar results applied to the survivability of venture-backed IPOs conditional on delisting. The data span 1995-2009. Source: CRSP/Capital IQ Merged.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Merger Event</th>
<th>Delisting Event</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log-Likelihood</td>
<td>AIC</td>
</tr>
<tr>
<td>Exponential</td>
<td>-3935</td>
<td>7886</td>
</tr>
<tr>
<td>Weibull</td>
<td>-3783</td>
<td>7584</td>
</tr>
<tr>
<td>Lognormal</td>
<td>-3693</td>
<td>7404</td>
</tr>
<tr>
<td>Loglogistic</td>
<td>-3755</td>
<td>7528</td>
</tr>
</tbody>
</table>

Once again, the lognormal distribution best fits the model in both events. The results of the competing risk lognormal regressions for the test variable Early Stage are contained in Table 22. The control variables (with the exception Yearly IPO Activity in the Merger Event) each see their significance improve and the direction of the variables is consistent with the Cox model as well as the regressions performed for the Specialist test variable. The test variable, Early Stage, remains statistically insignificant with a sign opposite of the
hypothesis (note again that the change from a proportional hazard model to an accelerated failure time metric changes the way the variables are interpreted—the negative coefficients imply a decrease in survival time).

The data find no statistical relationship between early stage investors and investors which invest across different stages. One rationale for this could be that while a venture capital firm which invests in later stages as well as early stages may understand well the growth cycle of young firms; the effects are not translated into post-IPO operational improvement.

A second rationale for the slight (statistically insignificant) reduction in hazard in the delisting case may be from the investment rationale of a firm which solely invests in early stage. These firms may be more eager to get out of the business as the payday is further off

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Merger Event</th>
<th></th>
<th></th>
<th>Delisting Event</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Effect on time to Failure</td>
<td>Standard Error</td>
<td>P&gt;</td>
<td>z</td>
<td></td>
<td>Effect on time to Failure</td>
</tr>
<tr>
<td>Early Stage VC</td>
<td>-.044</td>
<td>.051</td>
<td>.93</td>
<td>-.053</td>
<td>.065</td>
<td>.42</td>
</tr>
<tr>
<td>Age of Offering</td>
<td>-.004**</td>
<td>.011</td>
<td>.01</td>
<td>.007**</td>
<td>.002</td>
<td>.00</td>
</tr>
<tr>
<td>IPO Transaction Value</td>
<td>.001**</td>
<td>.000</td>
<td>.00</td>
<td>.000**</td>
<td>.000</td>
<td>.01</td>
</tr>
<tr>
<td>Yearly IPO Activity</td>
<td>.000</td>
<td>.000</td>
<td>.83</td>
<td>.000**</td>
<td>.000</td>
<td>.00</td>
</tr>
<tr>
<td>Lagged Industry Returns</td>
<td>-.052</td>
<td>.079</td>
<td>.51</td>
<td>-.071</td>
<td>.098</td>
<td>.47</td>
</tr>
<tr>
<td>Underwriter: Top Tier</td>
<td>-.616**</td>
<td>.143</td>
<td>.00</td>
<td>.861**</td>
<td>.114</td>
<td>.00</td>
</tr>
<tr>
<td>Underwriter: 2nd Tier</td>
<td>-.689**</td>
<td>.144</td>
<td>.00</td>
<td>.933**</td>
<td>.118</td>
<td>.00</td>
</tr>
<tr>
<td>Constant</td>
<td>3.126**</td>
<td>.145</td>
<td>.00</td>
<td>2.155**</td>
<td>.113</td>
<td>.00</td>
</tr>
<tr>
<td>Sigma</td>
<td>1.014</td>
<td>.020</td>
<td>.00</td>
<td>1.157</td>
<td>.029</td>
<td>.00</td>
</tr>
</tbody>
</table>

* Significant at 5% ** Significant at 1%
than a firm which has some of its portfolio invested in start-ups which are closer to initial public offering exits. The firms that have the longer duration in their investments could face added pressures to achieve exits. This could lead to a kind of “grandstanding,” where firms are pushed to public offering before their time. Grandstanding is correlated with long run underperformance. Further investigation may yield better results. A follow-up study comparing early-stage-only venture capital’s IPO performance to later-stage only venture capital’s IPO could help to establish, if any, a link.

3.5.4 Test Variable: Single Stage

The final test variable is singlestage. It attempts to establish, if any, correlation between venture capital firms which focus due diligence and initial investments on one stage of the start-up life cycle (e.g., Seed or Growth or Mezzanine) and subsequent IPO survival rates and lifespan. The control group will be venture capital firms which invest initially across more than one stage of entrepreneurial development. As with previous tests variables, the results for nonparametric and semi-parametric regressions are relegated to Appendix B.

Parametric Regression

To determine the best fit for the data, the Akaike Information Criterion is calculated. Table 23 presents the results which are almost identical to the earlystage calculations. This is not unexpected as while there is low correlation between the variables earlystage and singlestage (Correlation = .29), both add little information to the model. Thus the AIC results will be similar for both cases.
In both the merger event and delisting event, the lognormal distribution receives the lowest AIC score. The regression results of the lognormal distribution are presented in Table 24.

A single stage venture capital fund seems to have no effect on an IPO’s probability of being acquired and may actually decrease time to failure, though the effect is not statistically significant. The data reject Hypothesis 3.

---

Table 23:
Akaike Information Criterion, Single Stage Test Variable

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Merger Event</th>
<th>Delisting Event</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log-Likelihood</td>
<td>AIC</td>
</tr>
<tr>
<td>Exponential</td>
<td>-3935</td>
<td>7886</td>
</tr>
<tr>
<td>Weibull</td>
<td>-3783</td>
<td>7584</td>
</tr>
<tr>
<td>Lognormal</td>
<td><strong>-3693</strong></td>
<td><strong>7404</strong></td>
</tr>
<tr>
<td>Loglogistic</td>
<td>-3755</td>
<td>7528</td>
</tr>
</tbody>
</table>

Table 24:
Parametric Regression Results, Lognormal Distribution – Single Stage Test Variable

| Covariate                  | Merger Event | Delisting Event | P>|z| | P>|z| |
|----------------------------|--------------|-----------------|-------|-------|
| Time to Failure            | Std. Error   | Time to Failure | Std. Error | std. Error | Time to Failure | Std. Error | std. Error |
| VC Single Stage            | 0.031        | 0.058           | .60    | -.074  | .074    | .32         |
| Age at Offering            | -0.004*      | 0.001           | .00    | .007** | .002    | .00         |
| IPO Transaction Value      | 0.000**      | 0.000           | .00    | .000** | .000    | .00         |
| Yearly IPO Activity        | 0.000        | 0.000           | .83    | .000** | .000    | .00         |
| Lagged Industry Returns    | -0.053**     | 0.079           | .51    | -.071  | .098    | .47         |
| Underwriter: Top Tier      | -0.616**     | 0.143           | .00    | .861** | .114    | .00         |
| Underwriter: 2nd Tier      | -0.689**     | 0.144           | .00    | .933** | .118    | .00         |
| Constant                   | 3.122**      | 0.145           | .00    | 2.155**| .113    | .00         |
| Sigma                      | 1.014        | 0.020           |       | 1.157  | .029    |             |

* Significant at 5% ** Significant at 1%

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44 Note the similarities to the results with variable “earlystage.” This is not surprising, since there is only one change in the manner of classification of one variable (early stage to single stage).
3.6 Conclusion

This study uses a unique dataset not used before. It merges Capital IQ private equity data with CRSP public equity performance results. The results show that industry knowledge that comes with a venture capital firm which specializes enhances the survivability and the returns of initial public offerings. The data are inconclusive on the benefits of venture firms which invest across stages of entrepreneurial development against those which invest in a single stage or early stages only. Underwriter prestige strongly supports the performance and survivability of initial public offerings.

The results are useful to a variety of investors. Limited partners seeking out venture capital as a part of their portfolio will benefit from a better understanding of which venture capital attributes contribute to more successful exits. Understanding what drives IPO performance will help any investors to make better decisions when investing in IPOs. Finally, entrepreneurs who are considering venture capital can benefit from these results by helping in the selection process of which VC funds to approach.
Appendix A Capital IQ Data Setup

Working with the Capital IQ database provided both a challenge and a unique opportunity. The challenge is building an academic dataset from a database designed primarily for industry users. The dataset constructed provides a second source available to researchers. Results can be compared to the other major sources of private equity data.

Currently, Thomson VentureXpert is the strongest source of data. The dataset is robust back to the mid-1970s and provides comprehensive data on private equity (buyouts) and venture capital. A second data source is Cambridge Associates. Cambridge Associates provides investment research and consulting to the endowments of U.S. universities. Aggregate performance data are available to the public. Individual fund characteristics and performance are available to members. Granular data are considered proprietary and not available for this research.

Sandhill Econometrics built a dataset that its founder, Susan Woodward, used to construct an unbiased venture capital index for Dow Jones. The creation of the dataset addresses many of the biases inherent in the valuation of non-publicly traded endeavors. The index is used as a benchmark in Chapter 1 of this thesis. Unfortunately this data set is also proprietary with access limited to the Sandhill Econometrics group.

The dataset created here is narrower in focus than the scope of the other private equity databases. It matches venture capital funds and their characteristics to portfolio companies backed by those VCs that went public. The decision to use Capital IQ in lieu of
VentureXpert comes from a beneficial anomaly found in Princeton’s access to Capital IQ. The data in Capital IQ can display a column not typically available for most users of Capital IQ which tags each IPO with its Compustat permanent identifier number, known as the GVKey. Using the GVKey in the matching process bypasses manually matching an IPO with its parent Venture Capital firm. The advantage of this dataset is that all performance numbers come from publicly traded companies (the IPOs) and the robust CRSP/Compustat databases. The use of public data eliminates any of the reporting biases that may be present in reporting by venture capital firms.

This appendix will walk through the steps necessary to convert the Capital IQ data into a dataset that is ready for use in some statistical software (specifically Stata). There were two screenings that took place using the Capital IQ platform. The first was a simple data extraction of all IPOs that occurred within the United States during the sample time period (1995-2009). Though the IPO data go back to 1968 (Rite Aid’s IPO of $8.75 million) conversations with Capital IQ analysts confirmed the skepticism that the data were not complete. According to Capital IQ, data from the early 1990s is fairly extensive; however, it is not until the mid-1990s that the data are considered complete. The screening included a number of data points (such as IPO industry identification and IPO transaction value) and was used as a check against the CRSP IPO data, ensuring that the data line up. However, its primary function is to link the IPO name to its Compustat identifier (which will then be linked to its CRSP identifier). The Compustat identifier is known as the GVKey.
The GVKey is Compustat’s permanent identifier for a company. Like the Permno of CRSP, the GVkey will not change over time (unlike, for example, the company’s CUSIP). Compustat and Capital IQ are divisions of Standard & Poor, however, there GVkey output is typically not available to Capital IQ subscribers. Through the efforts of Todd Hines, Research Librarian at Princeton University, access linking the GVKey Capital IQ’s company data has been made available. As of this writing, neither the author nor Mr. Hines is aware of any other academic university which offers this unique linking system.

The second screening sourced from Capital IQ provides an extensive snapshot of Venture Capital firms in the U.S., both past and present. Capital IQ uploads considerable data on its “tearsheets” (the one page company summary) of venture capital firms. While the data are worldwide, the study selects U.S. VC firms for the richness and consistency of available data. Capital IQ reports key attributes of a Venture Capital firm such as its Limited Partners, the intended fund type (e.g., early, middle or late stage), areas of industry interest, dates of fund formation and current and prior investments. Any non-U.S. VC firm whose primary purpose is not venture capital (but happen to have a VC branch) is filtered out. This leaves 3,100 firms in the Venture Capital section of the dataset. Please see Table A1 for two sample VC firm and their descriptors.

In Table A1, column A lists the venture capital firm’s name. To retain the unique relationship between VC and each IPO, a unique VC identifier column is matched to each venture capital name. Column B lists the limited partners that have committed capital to the venture capital firm.
The Capital IQ database only presents the first 244 characters of the list of limited partners. For firms like Sequoia Partners, with many more limited partners than room available, Capital IQ simply cuts off the list at 244 characters. The data can only be retrieved for these firms by going to the individual firm’s “tearsheet” (the detailed summary of each firm in Capital IQ). Herein lies the difficulty with working with Capital IQ as this format holds for all of the variables in the dataset.

Also, care must be taken as Capital IQ lists all limited partners, making only the simple distinction between current limited partners and prior limited partners. The date of departure as a limited partner could be vital information for a researcher. For example, the investment world viewed Accel Partners very differently before and after Princeton University (and other endowments) withheld capital commitments for future funds (and very differently again after the Facebook IPO). Columns C and D show the number of
current and prior investments. These are defined as portfolio companies within (at least one) of the venture capital firm’s funds. Academic studies using fund level data beware, these data points make no distinction as to which fund each investment belongs.

Industry focus is described in detail in Column E. Here is a challenge and an opportunity. The challenge is the manner in which the data are presented. For example, Catalysts Ventures invests in Information Technology; Healthcare; Pharmaceuticals Biotechnology and Life Sciences; Biotechnology. The manner of reporting, some industry level responses (e.g., Healthcare) commingled with sub-industry level responses (e.g., Pharmaceuticals Biotechnology and Life Sciences), makes sorting and categorizing difficult. To address this, a search was done within each cell for each of the Capital IQ Global Industry Classification Standards (GICs); see Table 7 for the list. Fortunately, no VC firm listed a sub-industry without listing the general industry classification (e.g., if Pharmaceuticals Biotechnology and Life Sciences was present, so was Healthcare). Thus no data were omitted due to only sub-industry classification reported. The ten GICS translated fairly easily to the Fama-French twelve industry coding system used for generating the industry return control variable.

The venture capital firms also report the stages of finance in which they invest to the Capital IQ database. For example, Alpine Technology Ventures provides financing only at the early and growth stages of the start-up life cycle. On the other hand, Catalysts Ventures invests in companies at the seed stage up to the late venture stage and stages in between. Reporting here was standardized, so the sorting process was not difficult.
The key cell in this screening is contained in Column G. Here Capital IQ lists the company names of all of the initial public offerings which were funded by the Venture Capital firm. For example, Alpine Technology backed the IPO of Eon Communication Inc. On the other hand, Catalyst Ventures had no initial public offerings during the time frame of the study.

The first major obstacle to the construction of the data set is here. The use of the company name is bereft with matching problems, as each database (Capital IQ, Compustat and CRSP) may have subtle differences in the way it records the company’s name. For example, the company Eon Communications, Capital IQ calls it “Eon Communications Inc.;” but CRSP may (for the sake of argument) record the same company as “Eon Comm. Incorporated.” Even subtle changes will cause problems with the matching process, so the need for objective numerical identifiers is critical. To transform the IPO’s company name into its corresponding GVkey, the first Capital IQ screen will be used. However, before this can occur, Capital IQ’s cell size limitation must be addressed here.

When the Capital IQ screening reports the VC’s IPO investments, it includes, alphabetically, the first 244 characters of IPO names. Thus any VC firm with a larger number of IPOs will only list the first few. In this study, out of 3,100 VC firms in the sample, 559 companies had IPO investments which were truncated by Capital IQ. Each of these VC firm’s IPO companies were hand collected from the Capital IQ tearsheets and added to the overall dataset.

AND SO CALLED “FUZZY SEARCHES” AND “FUZZY LOOKUPS” WERE DEPLOYED UNSUCCESSFULLY.
After some further data preparation⁴⁶, the next step of the conversion process uses both the first Capital IQ IPO screening (for all IPOs in the Capital IQ database) and the second Capital IQ VC screening. Each cell in the second screen’s Column G was searched for any IPOs listed in the first screening⁴⁷. If a match is found the company’s GVKey is reported in a separate cell. The GVkeys, which are now broken into separate columns, must be concatenated (recompiled into single cells) for the next step of the process, delimited by a single space between each GVKey⁴⁸.

Recall again the truncation which occurs at the 244 character mark in the Capital IQ cells. The GVkey is a four to six digit identifier. Recall that the maximum number of characters in each of the Capital IQ cells is 244. Thus when compiling these GVkeys, care must be taken to make sure no IPO investments are missed, especially for companies with more than about 35 to 37 IPOs. For example, Accel Management reported (as of 12/31/2009) 39 initial public offerings to Capital IQ.

In this study, 32 venture capital firms had more than 35-37 IPOs. With care to ensure that GVKeys were not cut off (due to differing sizes) in the concatenation process, a maximum of three cells worth of GVKeys was necessary to list all IPOs for each venture capital firm.

At this point, the VC data must now be matched with IPO performance numbers from the Center for Research in Security Prices (CRSP).

⁴⁶ For example, special characters such as “.” and “@” are removed or modified.
⁴⁷ It is recommended that if the data are replicated, breaking the VC firms into smaller subsets of approximately 300 firms or less may help keep the processing time/computer lockup concerns.
⁴⁸ Special thanks to McGimpsey & Associates for the Excel user-defined function “Multicat” which is able to do what Excel’s Concatenation function is unable to do.
The public data are primarily sourced from CRSP\textsuperscript{49}. The CRSP screening in this dataset collects all initial public offerings performance data in the United States during the sample period (January 1, 1995 to December 31, 2011). The performance data are reported monthly as holding period returns with dividends included. Once the performance returns (one year, annualized three year and annualized cumulative returns) are calculated, the data are merged with the Capital IQ dataset. This is accomplished using the Compustat/CRSP Merged database linking table. This linking table matches GVKeys with their corresponding CRSP permanent identifier, the Permno. Please see figure A1 for a graphical depiction of the creation of the dataset.

\textsuperscript{49} The IPO data pulled from Capital IQ screening provide a “check” for consistency, a backup for missing data and a verification that the matching techniques employed are accurate.
Appendix B Survival Analysis and Competing Risks

This appendix provides a brief discussion on the adaptation of VC/IPO data to survival analysis. In standard survival analysis the survival indicator marks the data whether or not the data have experienced a failure event. Within survival analysis, failure is defined as permanent removal from the data pool. The failure event is not necessarily a bad outcome.

The CRSP delisting codes provide guidance into what is survival and what is failure. As described in Table 7, there are five general categories of IPO status. All codes in the 100 range are actively traded. All codes in the 200 range have been acquired or have merged with another firm. Within the context of this study, the firm is no longer part of the IPO framework. This is the case whether or not the firm remains merged or is spun-off later. Even if the company is spun-off with the same name and intent as the original IPO, the influence of the original venture capital “parents” is negligible at this point.

All codes in the 300 range indicate an issue exchange for an issue traded on another exchange. This could be a good occurrence or a bad occurrence. If the firm wishes to move laterally, say from the NASDAQ to the NYSE, then the exchange code implies neither a negative outcome nor a failure event as previously defined. If the move is from the NYSE to the Pink Sheets, then this is certainly both a negative outcome and a failure event (since the OTC Markets Group is not considered a stock exchange). Fortunately this ambiguity is not of any concern to this study as none of the data which makes it through the screening process has any coding in the 300 range.
The 400 coding range indicates liquidations. Only one data point earned a code 470 (Issue Liquidated, no final distribution verified). This data point was folded into the final category, the delisting events. The delisting events, most 500 level codes, are generally considered bad outcomes. The IPO fails to meet some specific trading requirements of the exchange and is dropped. Some of the 500 level codes, specifically 501-519, did not fit the delisting paradigm and were dropped. They indicated the issue stopped trading on the current exchange and moved to a new exchange. This is not necessarily a bad outcome. No companies reaching the final screening coded in this range. Code 520, the move from the exchange to the over-the-counter market remained as this implied a “bad outcome.”

Within the survival framework of the statistical package used in this research, Stata, the survival indicator variable takes on special meaning. A “0” implies survival through right-censoring (the data set ends before failure can occur). A “1” implies a failure event. The model in this analysis starts with some ambiguity, as in the competing risks framework a “1” could imply either a merger event or a delisting event. Using an additional indicator variable, dlstcde, Stata is able to properly and seamlessly account for these competing risks. The categorical dlstcde has three categories: 2 – delisting event, 1 – merger event, 0 – survival event. That said, about 52% of the 5,740 observations survive (remain actively traded as of 12/31/2009). About 30% of the IPOs merge during the time framework and about 18% fail due to a delisting event.

50 In the competing risks framework a variety of types of failure can occur (an IPO can be merged with another firm, delisted or liquidated). Once failure occurs, though, it is irreversible (once an IPO is acquired by another firm it ceases to be only that venture-backed IPO.
Appendix C: Nonparametric Analysis and Semi Parametric Analysis

Test Variable Specialist

With no functional form, nonparametric analysis is a good place to begin survival analysis. It allows the data to speak for itself, as no underlying assumptions are made about the shape of the hazard function. Nonparametric analysis also assumes nothing about the distribution of the covariates of the model.

The Kaplan-Meier hazard estimates provide some interest insight into the nature of the effects of the specialist VC backed IPOs. Figure C1 shows that IPOs with Specialist VC-backing have a significantly lower risk of delisting during the early years of public trading. In fact, the model shows that no delisting events occur until at least the second year of public existence for these firms. By about the 7\textsuperscript{th} year, the effects seem to reverse. At this point the level of expertise that the specialist has imparted to the IPO (which is now maturing into its 7\textsuperscript{th} year) may have a negative influence on its survival rate. There is an additional reversal at about year 12. It could be a statistically insignificant reversal. The overall effect is to reduce the risk of failure.
On net, the survival function and the concurrent results show a positive relationship between specialist and IPO survival. Figure C2 is the stepwise representation of the Kaplan-Meier nonparametric survival function. Note that Figure C2 has a horizontal asymptote above 0. This follows since about 52% of the observed data survive and under the competing risks framework, those firms that were merged and not delisted were considered censored as well. The risk table is presented beneath the graph in Figure 8.
Semi-parametric Model

The model establishes the positive relationship between specialist and survival in the context of the risk of delisting. The advantage of nonparametric analysis is that it is most flexible in its construction and it lets the data speak for themselves. That said, semi-parametric analysis is necessary to generate coefficients for test and control variables. The study uses the Cox proportional hazards regression to explore these coefficients under both cause-specific risks—the risk of a delisting event and the risk of a merger event. Cox (1972), who assumes that the covariates multiplicatively shift the baseline hazard function, posits that that the hazard rate is:

$$h(t | x_i) = h_0(t) \exp(x_i \beta)$$  \hspace{1cm} (11)$$

where $h(t | x_i)$ is the hazard function given a vector of covariates $x_i$. This vector of covariates includes the test variable (Specialist, Early Stage or Single Stage) and the set of

Figure C2: Kaplan-Meier Hazard Estimate – Specialist

This graph shows the survival function for IPOs under the risk of delisting. The solid line represents the hazard estimate for a VC specialist and the dashed line represents the hazard rate for a VC generalist. The data range from 1995-2009. Source: CRSP/Capital IQ Merged

Number at risk

| specialist = 0 | 4392 | 2038 | 626 | 0 |
| specialist = 1 | 827  | 393  | 107 | 0 |

analysis time

VC Generalist VC Specialist

This graph shows the survival function for IPOs under the risk of delisting. The solid line represents the hazard estimate for a VC specialist and the dashed line represents the hazard rate for a VC generalist. The data range from 1995-2009. Source: CRSP/Capital IQ Merged

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control variables (age at offering, IPO transaction value, yearly IPO activity, industry performance and underwriter prestige). The baseline hazard, $h_0(t)$ assumes that all covariates are zero (and in the Cox model needs no parameterization). The data estimate the row vector, $\beta_x$. See Table C1 for the results of this regression and the implied hazard ratios (the column $\hat{\beta}$ contains the estimated coefficient).

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Merger Event</th>
<th></th>
<th></th>
<th>Delisting Event</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hazard Ratio</td>
<td>Standard Error</td>
<td>P&gt;</td>
<td>z</td>
<td></td>
<td>Hazard Ratio</td>
</tr>
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<td>VC Specialist</td>
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<td>.29</td>
<td>0.820*</td>
<td>0.078</td>
<td>0.03</td>
</tr>
<tr>
<td>Age at Offering$^{51}$</td>
<td>1.004</td>
<td>.002</td>
<td>.06</td>
<td>0.988**</td>
<td>0.004</td>
<td>0.01</td>
</tr>
<tr>
<td>IPO Trans. Value</td>
<td>0.999**</td>
<td>.000</td>
<td>.00</td>
<td>1.000</td>
<td>0.000</td>
<td>0.06</td>
</tr>
<tr>
<td>Yearly IPO Act.</td>
<td>1.000</td>
<td>.000</td>
<td>.93</td>
<td>1.000**</td>
<td>0.000</td>
<td>0.00</td>
</tr>
<tr>
<td>Lagged Industry Perform.</td>
<td>1.187</td>
<td>.134</td>
<td>.13</td>
<td>1.195</td>
<td>0.162</td>
<td>0.19</td>
</tr>
<tr>
<td>Underwriter: Top</td>
<td>2.610**</td>
<td>.640</td>
<td>.00</td>
<td>0.344**</td>
<td>0.042</td>
<td>0.00</td>
</tr>
<tr>
<td>Underwriter: 2nd</td>
<td>2.941**</td>
<td>.726</td>
<td>.00</td>
<td>0.349**</td>
<td>0.046</td>
<td>0.00</td>
</tr>
</tbody>
</table>

* Significant at 5%   ** Significant at 1%

Please note the difference in the way hazard models are interpreted. A hazard ratio of greater than one indicates that the independent variable increases the hazard rate in the dependent variable. A score of less than one implies that the risk of failure decreases when the treatment (in this case- a venture capital firm which specializes) is applied.

---

$^{51}$ Age of Offering, IPO Transaction Value and Yearly IPO Activity have been centered to generate a true baseline hazard function.
For both competing risks, the control variables behave in mostly expected ways. *Age at Offering* offers no statistically significant effect on the probability of a merger but does slightly decrease the probability of a delisting event, significant at 1%. This result is supported by the literature (see Ritter [1991], for example).

*Lagged Industry Performance* in the year of the IPO does increase the hazard rate of an IPO experiencing a merger event and a delisting. However, in both cases, the effect is statistically insignificant. This makes sense as a better performing industry is more likely to have generate greater external interest in acquisitions and mergers as well as a greater likelihood of the existence, internally, of bubbles.

*Underwriter Prestige* is the categorical variable with three categories (Top-Tier, 2nd Tier and Other). The results of the competing risk models agree with the literature and common sense. IPOs backed by top-tier and 2nd tier underwriters are both more likely to experience merger events. Likewise, IPOs with better underwriter backing experience delisting failure at a rate of about 35% of firms which have no such backing. The results agree with Loughran and Ritter (2004). This is significant at the 1% for both competing risk regressions. On the other hand, underwriter prestige is positively and significantly correlated with a merger event. This makes sense, as backing by, say, Goldman Sachs, generates considerable interest in an IPO. Some of this interest is acquiring an IPO backed by a top-tier underwriter.
In the context of the failure defined as a merger, a venture capitalist which specializes in one industry will decrease the probability of failure (a merger or acquisition) but not by a statistically significant amount. On the other hand, the risk of delisting is reduced, significant at 5%. The rate of observing a failure if the IPO is backed by a specialist venture capital fund is 81% of the rate of observing a failure of an IPO backed by a generalist venture capital fund.

**Test Variable Early Stage**

Nonparametric Model: Figures C3 and C4 depict the Kaplan-Meier Survival Estimates for the test variable Early Stage for both the Merger and the Delisting events. For the risk of merger, graphically, there does not appear to be any strong increase (or decrease) in survival. The treatment group (Early Stage) fluctuates above and below the control group (Other-Stage). By the end of the sample, the control group-backed IPOs had a higher survival rate than those backed by Early Stage venture capitalists.

![Figure C3: Kaplan-Meier Hazard Estimate – Early Stage, Merger Event](image)

This graph shows the survival function for IPOs under the risk of acquisition. The solid line represents the hazard estimate for early stage VC and the dashed line represents the hazard rate for other stage VC. The data range from 1995-2009. Source: CRSP/Capital IQ Merged.
Risk of delisting has consistent, though not very strong, results that contrast Hypothesis 2. The control group (Other-Stage) actually sees its IPOs outlive the treatment group’s public companies. The study next presents the semi-parametric and parametric regressions to verify and test for significance.

Figure C4: Kaplan-Meier Hazard– Early Stage, Delisting Event
This graph shows the survival function for IPOs under the risk of delisting. The solid line represents the hazard estimate for early stage VC and the dashed line represents the hazard rate for other stage VC. The data range from 1995-2009. Source: CRSP/Capital IQ Merged

Semi-parametric Model: The nonparametric model suggests that there is no significant link between the test variables earlystage and IPO survival. To verify this, the study focuses on both competing risks using the Cox regression. The study compares this regression’s control variable results to the results from the regression with specialist as the test variable, to confirm consistency. See Table C2 for the results.

The test variable is not statistically significant in either of the events. However, the results for a delisting event are consistent with Hypothesis 2. The control variables behave similarly to the regressions performed in the specialist case. One interesting change is the
significance of Yearly IPO Activity for the Merger case. When the Early Stage variable is included, Yearly IPO Activity ceases to be significant. This could suggest some collinearity between these variables, though a reason is not readily apparent.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Merger Event</th>
<th>Delisting Event</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hazard Ratio</td>
<td>Standard Error</td>
</tr>
<tr>
<td>Early Stage VC</td>
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<td>.071</td>
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<tr>
<td>Age of Offering</td>
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<td>.002</td>
</tr>
<tr>
<td>IPO Transaction Value</td>
<td>.999**</td>
<td>.000</td>
</tr>
<tr>
<td>Yearly IPO Activity</td>
<td>1.000</td>
<td>.015</td>
</tr>
<tr>
<td>Lagged Industry Return</td>
<td>1.190</td>
<td>.134</td>
</tr>
<tr>
<td>Underwriter: Top Tier</td>
<td>2.866**</td>
<td>.724</td>
</tr>
<tr>
<td>Underwriter: 2nd Tier</td>
<td>3.236**</td>
<td>.822</td>
</tr>
</tbody>
</table>

* Significant at 5%  ** Significant at 1%

**Test Variable Single Stage**

Nonparametric Model: The results of the nonparametric model for the test variable singlestage are similar to the results generated from earlystage. In Figures C5 and C6, the results seem to indicate that there is no real link between the risk of a merger event and the decision for a firm to focus due diligence in one stage of start-up development. This decision to exclude all other areas of focus actually seems to increase the risk of delisting, though, as the Cox regressions will show, the result is not statistically significant.
Semi-Parametric Model

To estimate the size of the effect of the covariates in the model, focusing on singlestage, return again to the Cox regression to generate the covariate coefficients. Table C3 contains the details. The results are consistent with the results listed in the earlystage section. A firm which focuses on investing in just one stage of start-up firms actually shows a tendency, though statistically insignificant, to parent initial public offerings with increased
probability of delisting. This “single stage” VC also has no statistical effect on the lifespan of a firm which ends in an acquisition.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Merger Event</th>
<th>Delisting Event</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hazard Ratio</td>
<td>Standard Error</td>
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<tr>
<td>Single Stage VC</td>
<td>0.941</td>
<td>0.079</td>
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<tr>
<td>Age at Offering</td>
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<td>0.002</td>
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<td>IPO Transaction Value</td>
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<td>Yearly IPO Activity</td>
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<tr>
<td>Lagged Industry Returns</td>
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<tr>
<td>Underwriter: Top Tier</td>
<td>2.865</td>
<td>0.813</td>
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<tr>
<td>Underwriter: 2nd Tier</td>
<td>3.233</td>
<td>0.876</td>
</tr>
</tbody>
</table>

* Significant at 5%  ** Significant at 1%
References


