Portfolio Industry Strategy in Venture Capital Investments

LUCIA SILVA GAO

LUCIA SILVA GAO is an assistant professor of finance in the College of Management at the University of Massachusetts Boston in Boston, MA.
lucia.silva-gao@umb.edu

As with investments in financial markets, venture capitalists (VCs) seek to maximize returns and minimize risk in their portfolios of investments. However, mechanisms to create value and manage risk in venture capital investments are by some means different from the ones used by portfolio fund managers. VCs must decide which individual investments to undertake. Decisions at the level of individual investments are generally based on its potential return and likelihood of a successful exit through an initial public offering (IPO) or merger and acquisition (M&A). Since most VCs make several investments, they must also make decisions across investments and on how to choose the composition of their portfolio of investments. Therefore, VCs make decisions both at the level of the portfolio companies and at the level of portfolio composition and strategy.

Unlikely portfolio fund managers, VCs can have an active management role in the companies invested in their portfolios. Elango et al. [1995] distinguish between three categories of venture capitalists: the "inactive" investors, the "active advice givers," and the "hands-on" investors. Venture success is often attributed to the amount and nature of the expertise the VC possesses (Dimov and Shepherd [2005]), VCs' oversight and board representation (Lerner [1995]), and involvement in management recruiting and human resource policies (Hellmann and Puri [2002]). VCs' portfolio composition and strategy is likely related to differences in terms of VC expertise and degree of involvement in the management of portfolio companies.

VCs portfolio strategy can entail specialization or diversification. The "specialist" VC invests in companies and/or funds that are similar in their characteristics. The "generalist" VC invests in companies and/or funds that are heterogeneous in nature and follow a diversification strategy (Knill [2009]). VCs can specialize in terms of industry, development stage, or geographically (Gupta and Sapienza [1992]; Norton and Tenenbaum [1993]; Amit et al. [1998]; De Clercq et al. [2001]; Knill [2009]).

The advantages of portfolio specialization are related to reduction of information asymmetries, reduction of uncertainty, added expertise, knowledge and experience, and a better understanding of the complexities that are associated with particular development stages or industries (Gupta and Sapienza [1992]; Norton and Tenenbaum [1993]; Amit et al. [1998]; De Clercq et al. [2001]). VC specialization also facilitates the control that the VC exercises over the management of portfolio companies (Gupta and Sapienza [1992]) and makes it easier to detect the deterioration of the venture performance and to undertake timely corrective measures. Therefore, VCs' portfolio specialization can leverage the returns of the individual companies invested. Set against the advantages of specializations is the "cost" of reduced portfolio diversification.

A diversification strategy benefits from risk reduction by the same mechanisms of diversification described in the portfolio theory (Markowitz [1952]; Sharpe [1963, 1964]). The potential costs of diversification result from the limited nature of resources, both time and expertise. Depending upon the involvement style of the VC, diversification can entail considerable time and expense.

In this study I expand previous literature on VC portfolio strategy in terms of industry specialization versus diversification. More specifically, I look at portfolio performance for strategies of specialization in certain industries. Previous studies find evidence of better portfolio performance for strategies of industry specialization. For example, Gompers et al. [2008] found that investments made by VCs with a greater degree of industry specialization tended to be more successful, measured by a greater likelihood of profitable exit. Knill [2009] found that although VCs benefit with regard to their growth from following stage or industry diversification, the time to exit the portfolio companies in which they invest is delayed by such a strategy.

Additionally, I investigate if VCs pursue a strategy of exploiting synergies and complementarities between different portfolio companies. Complementarities and synergies can be found in different industries and at different levels. Companies can exploit complementarities at the inputs level, and joint efforts, for example, in research and development joint ventures. This study is applied to complementarities at the output level. Industries such as computer hardware, computer software, and communications are characterized by the existence of networks, where two or more components made by different manufacturers using different technologies may have to be used together, and systems have to be assembled. In this scenario, the value of each entrepreneurial firm's innovation depends on the success of the other firm's innovation.

Klier et al. [2009] list the exploitation of advantages of "portfolio relatedness" as one of the success factors of the "interventionist" VC, who takes an approach of active ownership. Value creation is driven by the centralization of resources that are critical to success, the consolidation of market access in areas of significant economies of scale, and by "actively liking portfolio companies with potential for cooperation." I investigate if VCs have an active role in coordinating investments by complementary entrepreneurial firms, and if the outcome of these investments is improved when VCs hold the complementary ventures in their portfolios.

The empirical examination of investment strategies and the resulting performance outcomes requires measures of specialization and complementarity. I analyze VCs' diversification versus specialization strategies by using the Herfindahl Index and the Index of Industry Specialization constructed based on the Venture Economics Industry Classification (VEIC) and on the industry aggregation proposed by Gompers, Kovner, Lerner, and Scharfstein [2008]. The measure of complementary network effects is based on the concept of "software stack" introduced in Gao and Iyer [2006], which proposes a representation of the organization of the software industry by different units that are related to the layers generally considered in software architecture.

When I consider the industry classification at the level proposed by Gompers et al. [2008], I find that VCs benefit from a strategy of industry specialization. The results also show that VCs' portfolios specialized in information technology, energy, or biotechnology outperform other portfolios. When I consider investments in information technology and communications classified at the level of the "software stack," the results are in the opposite direction: I find that diversified portfolios exhibit better performance. Rather than simply a diversification strategy, these portfolios may reflect a strategy of investing in complementary ventures. Additionally, I find evidence of value creation for VCs that follow this type of strategy.

This study contributes to the literature on VC strategy and performance and expands previous findings on portfolio specialization versus diversification. This research also provides new insights useful to venture capitalists, as they seek information on how to manage risk and create value in their portfolios, and to entrepreneurs, as they learn about the factors that venture capitalists consider in determining their investment strategy.

COMPLEMENTARY NETWORK EFFECTS

Network-type industries, particularly industries in information technology such as communications, semiconductors, software, and hardware, are characterized by the existence of complementarities and network effects.

Complementary network systems arise when different products that may require different technologies have to be used together. Although these technologies may be developed independently, they acquire much greater value when combined with those of other firms. Therefore, the value of each firm's innovation depends on the success of the other firm's innovation.

Within the software industry, companies deliver products that interoperate with complementary product components that are offered by other companies, and success is determined by network effects-based or system-based competition. These network effects can be derived from two sources: the degree of acceptance and adoption by customers, and the availability of complementary and supporting products. The first source is a direct or customer network effect and the second is a complementary or indirect network effect. Network effects have been widely discussed both in the economics literature (Farrell and Saloner [1985]; Katz and Shapiro [1985]; Economides and Salop [1992]; Shapiro and Varian [1999]) and within the information systems literature (see for example Cottrell and Koput [1998]).

Gao et al. [2008] discuss possible mechanisms to synchronize the innovations such that the various pieces of the system operate smoothly together and are available in a timely fashion. An example of such a network is the 3G-phone system. The launch of 3G required the coordinated investment of network operators, handsets, and applications. However, the lack of coordination led to failure of some of the enterprises. Network operators began to purchase the necessary spectrum and build out the networks in the late 1990s, but the lack of handsets and applications resulted in much lower than expected customer adoption. Gao et al. [2008] discuss different mechanisms through which firms developing complementary technologies may coordinate their investments, including mergers and acquisitions, equity investment, and cross-licensing. In this study, I investigate if VCs hold investments in different components of network systems and in this way play a role in the coordination of investments in complementary technologies.

EMPIRICAL DESIGN

Testing whether VCs benefit from different portfolio selection strategies requires measures of specialization or the existence of complementary network effects between the different ventures in the VC's portfolio, and measures of portfolio performance. The next sections describe the variables used in the empirical analysis.

Measuring Specialization versus Diversification

The measures of specialization are constructed based on the industry classification proposed by Gompers et al. [2008]. SDC provides a VEIC code for each entrepreneurial company in the sample. VEIC includes several levels of classification, from broader to more detailed, including 3 categories for Industry Class (Non-High Technology, Information Technology, and Medical/Health/Life Science), 6 industry major groups, 10 industry minor groups, 18 industry subgroups 1, 69 industry subgroups 2, and 572 industry subgroups 3, as represented by the companies in our sample. Gompers et al. [2008] combine this classification and arrive at nine broader industry categories: Internet and Computers, Communications and Electronics, Business and Industrial, Consumer, Energy, Biotech and Healthcare, Financial Services, Business Services, All Other. They consider that this classification scheme captures businesses that have similarities in technology and management expertise that would make specialization in such industries meaningful.

Gompers et al. [2008] measure specialization as the fraction of all previous investments that the VC made in a particular industry. I use two different measures to capture diversification versus concentration strategies in VC portfolios. The first measure is the Herfindahl-Hirschman Index (HHI) across industry categories. The index is calculated as follows:

$$\mathrm{HHI} = \sum_{i=1}^{n} p_i^2$$

where p_i represents the proportion of investment made in a particular industry. The larger the value of the index the larger is the level of specialization of the portfolio, with the maximum value of 1 representing specialization in a single industry.

The second measure of specialization is adapted from the literature on international trade and technology specialization (see Archibugi and Pianta [1994]) and used by Cressy et al. [2007] to capture specialization in a sample of private equity firms. The Index of Industry Specialization (IIS) is constructed as:

$$IIS_{ij} = \frac{(C_{ij}/C._{j})}{(C_{i.}/C_{..})}$$

where the dot indicates summation over, and

C_{ij} is the number of portfolio companies of VC firm i in industry j
$C_{.j}$ is the total number of companies invested in industry j
$C_{i.}$ is the total number of companies of VC firm i
C.. is the total number of companies invested by all VC firms

$$IIS_{ij} = \begin{cases} \geq 1 \Rightarrow (C_{ij}/C._{j}) \geq (C_{i.}/C_{..}) \\ < 1 \Rightarrow (C_{ij}/C._{j}) < (C_{i.}/C_{..}) \\ = 0 \Rightarrow C_{ij} = 0 \end{cases}$$

The numerator in this measure (C*ij*/C.*j*) represents VC firm i's share of all investments in industry *j* and the denominator (C*i*/C..) represents VC firm *i*'s share in all investments (i.e. across all industries). A value of IIS greater than one indicates that the VC firm is relatively specialized in a specific industry.

Measuring Complementary Network Effects

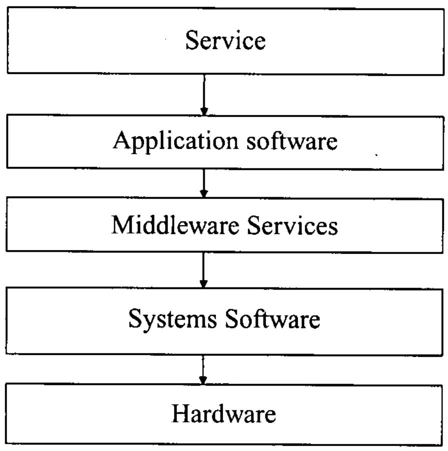
To test if VCs pursue a strategy of investing in complementary investments in information technology I use the concept of "software stack" introduced in Gao and Iyer [2006]. This concept is adapted from the software architecture and defines the structure of the software industry by the following layers: Hardware, Systems Software, Middleware Software, Applications Software, and Services. The application of this concept is premised on the idea that the organization of the software industry can be represented by different units that are equivalent to the ones considered in software architecture. Each software unit provides a cohesive set of services that other software programs can utilize without knowing how these services were implemented. There is an order in this structure: each of these components is layered above the other, and communicates through more or less standard interfaces, with closer layers being more related to each other than layers that are further apart on the stack. Software developers usually focus on one or a few layers of the stack and rely on other developers to provide the requisite functionality in other layers.

The measure of network effects used is this research is the Herfindahl-Hirschman Index constructed based on the software stack classification depicted in Exhibit 1. This index, denoted by HHI.STACK, measures diversification/specialization across the layers of the software stack. The detailed classification of the VEIC Industry Subgroup 3 permits an easy codification according to the software stack definition. I included communications in the layer Hardware, since it is an "infrastructure" that will support the development of applications and services. Internet Content was classified as Services, and Internet Communications was classified as Hardware.

Portfolio Performance Measures

Following Dimov and Clercq [2006] and Hochberg et al. [2007], I compute successful exit rates, the fraction of portfolio's companies that have successfully exited via an IPO or M&A transaction. Given limitations on information available regarding the actual returns on VCs' investments, Gompers et al. [2008] consider that the best we can do is to determine whether the investment resulted in a profitable exit for the venture capital firm. This is the case if the company went public, through an IPO, or was acquired or merged.

EXHIBIT 1
The Software Stack



VC firms earn positive returns from only a small fraction of their portfolio companies that exit via IPO or sale to another company. Hochberg et al. [2007] consider that all else equal, the more successful exits a fund has, the larger will be its Internal Rate of Return (IRR). They found that exit rates are related to IRRs for a small sample of funds where IRRs had been disclosed. Therefore, I use successful exit rates as a proxy for portfolio performance.

I measure portfolio performance for a multi-year period. In a study of the performance impact of VC syndication for a sample of companies that received the first funding investment between 1980 and 1999, Hochberg et al. [2007] compute funds' exit rates as the fraction of a fund's portfolio companies that have been successfully exited via an IPO or M&A as of November 2003. Dimov and de Clercq [2006] compute failure rates of the VC's portfolio as the proportion of defaults among companies that have been added to the portfolio in a given year. Their measure of industry specialization is also based on first-time investments made in a particular year. I consider that portfolio strategy should be captured during a significantly long period of time and, therefore, compute the portfolio strategy measures and exit rates for a ten-year period, from 1995 to 2004.

Control Variables

Several control variables that proxy for factors that are likely to affect portfolio performance are included in the model. First, I control for the type of VC. Corporate VCs' investment strategies may be motivated by strategic objectives beyond mere financial gains (Gompers and Lerner [2000, 2001]; Dushnitsky and Lenox [2005]). Additionally, affiliates of financial institutions have less pressure to maximize returns in comparison with Independent VC firms, because they do not have to raise funding from third parties (Abbott and Hay [1995]). VCs that depend on government or other public organizations may pursue non-wealth-maximizing goals related to economic development or employment growth (Lerner [1999]; Cumming and Macintosh [2006]). The level and nature of the expertise of the VC also depend on the type of the VC and may be a significant determinant of venture success (Dimov and Shepherd [2005]). The model used in this study includes dummy variables that indicate if the VC is a corporate VC (CVC), an independent VC firm (excluded category), or other type of VC (OVC).

The size of the VC portfolio may also predict performance. Kaplan and Schoar [2005] found that larger VC funds have superior performance, where performance is measured from the cash inflows and outflows of the fund. Other studies control for size when analyzing portfolio or fund performance. For example Hochberg et al. [2007] include in their model the total amount of committed capital reported by the fund. Knill [2009] constructs a measure to proxy for portfolio size based on the number of companies in which the fund invested. The proxy for portfolio size in my model is the total number of companies in the portfolio (NCOMP).

There is evidence that less established VC firms are more likely to fail (Dimov and Shepherd [2005]; Dimov and de Clercq [2006]). Gompers et al. [2008] show that VC firms with more overall and industry-specific experience are more successful. Their measure of experience is based on the number of investments in previous years. Hochberg et al. [2007] derive four proxies for experience: the age of the VC firm, the number of rounds the firm has participated in, the cumulative total amount it has invested, and the number of portfolio companies it has backed. I use the age of the VC in years to proxy for experience (VC.AGE).

I also control for the VC's investment stage preference with the variable EARLY.STAGE, a dummy variable equal to one if the VC prefers to invest in an early stage of the venture. Cochrane [2005] shows that later-stage deals have less volatility than early-stage deals. Other studies, for example Kaplan and Schoar [2005] and Hochberg et al. [2007], control for fund stage focus.

Lastly, I control for the age of companies in the portfolios, counted as the time since the company received the first round of financing (COMP.AGE). Dimov and de Clercq [2006] control for the investment year in order to account for the possibility that investments made in a particular year may have faced more turbulent conditions, as it is the case of the exuberant period between 1998 and 2000. Controlling for the age of the companies also accounts for the fact that investments made in more recent years had not "enough" time to succeed.

DATA AND EMPIRICAL ANALYSIS

The sample of VC rounds of financing, portfolio companies, and VC firms was obtained from the SDC Platinum/VentureXpert database from Thomson

Financial. I downloaded all rounds of financing that occurred between January 1, 1995, and December 31, 2004. This time range includes a period of high investment intensity in information technology. The data include specific information about the portfolio companies, the VC firms, and details related to the rounds of investments.

I used the information available for each round of investment to determine the portfolio of companies for each VC firm. The initial sample includes 188,489 round/entrepreneurial company/VC firm observations. I sorted rounds of investment by VC in order to identify the portfolio of investments for each VC firm. I consider an observation to be the first record of a VC firm and portfolio company pair, i.e., the first time a VC invests in a particular company, and exclude follow-on investments in the same portfolio company.

For several observations in the data set, the VC or the company is classified as Undisclosed. I eliminated all VC firms classified as Undisclosed but kept entrepreneurial firms classified as Undisclosed, because SDC still provides other relevant information about the company, for example the industry in which it operates. Since the purpose of this study is to identify portfolio strategies with regard to industry of the companies within VC portfolios, all investments made by each VC firm should be accounted for. These criteria yield a sample with 132,440 rounds of financing/VC firm/entrepreneurial company observations, 35,879 entrepreneurial companies, and 6,219 VCs. In addition, I considered only VCs that have invested in three or more companies during the ten-year period under consideration. Gompers et al. [2008] limit their sample of VCs to firms that invested in more than three portfolio companies in a given year to capture "genuine venture capital firms." This approach could introduce some survivorship bias if the worst firms invest in less than three companies during the period under study. I repeated the analysis presented in the following sections for the initial sample and also for a sample of VCs that invested in at least five companies during the period under study and the results were not significantly different. The final sample of VCs includes 3,959 observations. Additionally, for the analysis with the "software stack," the VC is required to invest in at least two companies in information technology, to capture a strategy of investing in companies that are complementary components of network systems.

VCs were grouped into three categories: Corporate VCs (including type of VCs classified by Venture Economics as Corporate Venture Program and Corporate Subsidiary of Affiliate), Independent VC firms (including type of VCs classified by Venture Economics as Private Equity Firm Investing Own Capital, Incubators, Investment Management Firm/Finance Consulting Firms, Private Equity Advisor, or Fund Manager) and Other (including types of VCs classified by Venture Economics as Commercial Bank Affiliate or Subsidiary, Investment/Merchant Bank Subsidiary, or Affiliate and Federal Government Affiliated Program). The control variable CVC is an indicator variable for the VC being classified as Corporate VC, and the variable OVC is an indicator variable for the classification Other.

SDC provides the total round amount but does not provide details on how much each of the VC firms contributed to this value. SDC provides information on "Total known amount firm invested in company." However, after analyzing the data I found several missing values and concluded that this may not be a reliable value. Instead, I constructed the measures of specialization and stack index based on the number of companies invested by the VC in a particular industry.

The variable that proxies for portfolio size (NCOMP) is the number of companies in which the VC invested over the ten-year period considered in our sample. The variable that proxies for experience (VC.AGE) is the age of the VC firm in years and was computed based on information provided by SDC regarding the founding date of the firm and on web searches. The variable COMP.AGE is the average of the age of the companies in the portfolio, counted from the year of the first round of VC funding the company received. EARLY.STAGE is a dummy variable equal to one if the VC prefers early stages of development. This variable is constructed based on information provided by SDC in the field "Firm Investment Stage Preference."

Also from SDC, I downloaded information on venture-backed IPOs and M&As. I recorded the public status of each portfolio company at the time of the data collection.

As shown in Exhibit 2, three industry groups account for more than 60% of the companies in the sample: Internet and Computers accounts for 34%, Communications and Electronics for 17%, and Biotech for 11%. Companies in these industries also show a larger average number of rounds received, and a larger number of VCs per company, when compared with the remaining industries. Average exit rates are larger in

EXHIBIT 2
Distribution of Portfolio Companies by Industry in the Period of 1995–2004

Industry	No. of Companies	%	Average No. VCs per Company	Average No. of Rounds Received	% Exit via IPO or M&A	No. of Rounds of Financing
Internet and Computers	12,336	34%	3.6	2.6	32%	56,440
Communications and Electronics	6,211	17%	3.8	2.6	34%	29,513
Business and Industrial	4,837	13%	1.9	1.7	26%	8,834
Consumer	3,628	10%	2.0	1.8	27%	7,604
Energy	570	2%	2.0	1.9	43%	1,223
Biotech and Healthcare	4,109	11%	4.1	3.1	33%	20,603
Financial Services	2,177	6%	1.8	1.7	20%	4,332
Business Services	1,495	4%	2.0	1.8	27%	3,067
All other	516	1%	1.6	1.6	25%	824
All companies	35,879	100%	3.1	3.3	30%	132,440

EXHIBIT 3
Distribution of Portfolio Companies by Year When Company Received the First Round of Investment and by Industry

Industry	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
All companies – Proportion by year	4.2%	6.4%	6.5%	9.7%	13.3%	23.2%	11.6%	7.1%	8.6%	9.2%
Proportion by industry for each year:										
Internet and Computers	25.9%	26.7%	27.9%	26.1%	47.6%	48.7%	32.5%	26.6%	23.3%	20.5%
Communications and Electronics	16.8%	15.7%	15.9%	16.9%	15.9%	20.2%	20.1%	16.1%	14.3%	15.2%
Business and Industrial	17.5%	15.7%	17.0%	16.7%	10.4%	8.2%	11.2%	15.1%	18.4%	19.0%
Consumer	14.6%	12.5%	12.5%	13.6%	8.8%	6.0%	8.4%	10.5%	12.0%	13.5%
Energy	1.4%	1.0%	1.5%	2.1%	0.7%	0.9%	1.9%	2.5%	2.3%	2.8%
Biotech and Healthcare	13.5%	13.8%	15.2%	12.4%	8.0%	7.2%	12.3%	15.8%	15.3%	12.8%
Financial Services	5.6%	10.4%	5.3%	5.9%	3.9%	4.3%	7.5%	7.1%	7.2%	7.7%
Business Services	3.6%	3.0%	3.3%	4.3%	3.9%	3.8%	4.9%	4.8%	4.8%	5.2%
All other	1.2%	1.2%	1.3%	2.1%	0.8%	0.7%	1.2%	1.5%	2.4%	3.1%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

the Energy sector, followed by Communications and Electronics, Biotech and Healthcare, and Internet and Computers.

The sample provides evidence of a peak on VC activity during the period of 1999 to 2001, with 23.2% of the companies receiving the first round of investment in the year 2000. A closer look at the data shows that 48.7% of these entrepreneurial companies are in the Internet and Computers industry group. Investments in the Energy sector and in Biotech have been increasing in the most recent years (see Exhibit 3).

As shown in Exhibit 4, Independent VC firms account for 65% and Corporate VCs for 12% of the VCs in the sample. Corporate VCs invest, on average, in a lower number of entrepreneurial companies and have higher levels of specialization of their portfolios (average HHI is 0.607 for portfolios of corporate VCs and 0.472 for portfolios of independent VC firms). Independent VC firms have the larger average number of investments per portfolio and a larger percentage prefer early-stage investments, when compared with corporate VCs.

The average of the values obtained for the Index of Industry Specialization (IIS) suggests that VCs specialize

Exhibit 4

Portfolio Statistics

HHI is the Herfindahl-Hirschman Index across the industry categories proposed by Gompers, Kovner, Lerner, and Scharfstein [2008]. IIS is the Index of Industry Specialization for each industry category.

Industry	All firms	Independent VC firms	Corporate VCs	Other
No. of VCs	3,959	2,582	463	914
%	100%	65%	12%	23%
No. Companies per portfolio*	19.69	20.53	15.54	19.42
No. Investments per portfolio*	32.57	36.42	21	27.55
Exit rate*	34.45%	33.20%	40.69%	34.80%
% Prefer Early Stage	42.64%	47.79%	33.90%	32.49%
HHI*	0.479	0.472	0.607	0.433
IIS.IC-Internet and Computers*	1.161	1.142	1.481	1.051
IIS.CE-Communications and Electronics*	1.157	1.149	1.493	1.007
IIS. BI-Business and Industrial*	0.721	0.744	0.213	0.744
IIS.C-Consumer*	0.739	0.769	0.353	0.851
IIS.E-Energy*	0.852	0.852	0.644	0.960
IIS.BH-Biotech and Healthcare*	1.254	1.270	1.070	1.302
IIS.FS-Financial Services*	0.552	0.533	0.223	0.775
IIS.BS-Business Services*	0.701	0.723	0.429	0.775
IIS.AO-All other*	0.639	0.644	0.264	0.812

**Mean for all portfolios in the category.*

in Biotech and Healthcare (average IIS.BH is 1.254), Internet and Computers (average IIS.IC is 1.161), and Communications and Electronics (average IIS.CE is 1.157). Corporate VCs have larger levels of specialization in Internet and Computers and Communications and Electronics. Independent VCs specialize predominantly in Biotech and Healthcare.

The average exit rate for the portfolios in our sample is 34.45%. This value is very close to the value of 34.2% obtained by Hochberg et al. [2007] for the 1980 to 1999 period. In our sample, Corporate VCs' portfolios have higher exit rates (40.69% versus 33.20% for Independent VC firms).

Exhibit 5 presents statistics for the sample of portfolios that invested in more than two entrepreneurial

Exhibit 5

Portfolio Statistics for the Sample of VCs That Invested in at Least Two Companies in Information Technology

HHI.STACK is the Herfindahl-Hirschman Index across the industry classification of the "software stack" proposed by Gao and Iyer [2006].

Industry	All firms	Independent VC firm	Corporate VC	Other
No. of VCs	3,653	2,326	494	833
%	100%	64%	14%	23%
Stack exit rate*	34.85%	33.45%	41.76%	34.67%
Stack-Proportion Hardware*	39.64%	39.88%	38.15%	39.85%
Stack-Proportion Systems Soft.*	5.50%	5.34%	6.82%	5.25
Stack-Proportion Middleware Soft.*	5.04%	5.14%	4.73%	4.94%
Stack-Proportion Applications Soft.*	24.16%	24.71%	20.24%	24.95%
Stack-Proportion Services*	25.67%	24.93%	30.05%	25.12%
HHI.STACK*	0.491	0.482	0.526	0.497

**Mean*

EXHIBIT 6
Correlation Coefficients

EXIT is defined as the fraction of the VC's portfolio companies that have been successfully exited via an IPO or M&A. CVC is a dummy variable equal to one if the VC is a corporate VC. IND.VC is a dummy variable equal to one if the VC is an independent VC firm. OVC is a dummy variable equal to one for all other types of VCs. EARLY.STAGE is a dummy variable equal to one if the company prefers to invest in early stages of development. NCOMP is the number of entrepreneurial companies in the portfolio. COMP.AGE is the average of the age of the companies in the portfolio, counted from the year of the first round of VC funding the company received. VC.AGE is the age of the VC firm. HHI is the Herfindahl-Hirschman Index across the industry categories proposed by Gompers, Kovner, Lerner, and Scharfstein [2008].

	EXIT	CVC	IND. VC	OVC	EARLY. STG	NCOMP	COMP. AGE	VC. AGE	HHI
EXIT	1	0.119	−0.070	−0.012	−0.162	0.092	0.468	0.141	0.033
CVC	0.119	1	−0.498	−0.199	−0.064	−0.040	0.124	−0.047	0.215
IND.VC	−0.070	−0.498	1	−0.750	0.143	0.031	−0.086	−0.046	−0.044
OVC	−0.012	−0.199	−0.750	1	−0.112	−0.004	0.003	0.088	−0.114
EARLY.STAGE	−0.162	−0.064	0.143	−0.112	1	0.044	−0.157	−0.076	0.176
NCOMPS	0.092	−0.040	0.031	−0.004	0.044	1	0.112	0.159	−0.175
COMP.AGE	0.468	0.124	−0.086	0.003	−0.157	0.112	1	0.224	−0.005
VC.AGE	0.141	−0.047	−0.046	0.088	−0.076	0.159	0.224	1	−0.158
HHI	0.033	0.215	−0.044	−0.114	0.176	−0.175	−0.005	−0.158	1

companies in information technology. Exit rates for the companies in information technology resemble the exit rates computed for the general sample. The value of the HHI.STACK is similar for corporate VCs, independent VC firms, and other types of VC firms. The values of the index suggest some diversification across the different layers of the "software stack," with larger proportions of investments in Hardware, Applications, and Services.

RESULTS

The correlation coefficients presented in Exhibit 6 suggest a positive relationship between portfolio specialization strategies and portfolio performance. Portfolio exit rates are also positively correlated with the indicator variable for corporate VC (CVC), portfolio size (NCOMP), and VC experience (VC.AGE). The variable that defines portfolio specialization (HHI) is positively correlated with CVC, suggesting that corporate VCs' portfolios are more specialized, but negatively correlated with VC.AGE, suggesting less diversification in portfolios of more experienced VCs. The positive correlation coefficient between HHI and EARLY.STAGE implies that VCs that invest in early-stage investments are more specialized, and the coefficient of -0.175 with NCOMP suggests that larger portfolios are less specialized.

Exhibit 7 presents the regressions of exit rates on the variables that define portfolio strategy and control variables for other factors that are likely to affect portfolio performance. The results reinforce the previous observation based on the correlation coefficients that specialized portfolios exhibit superior performance. After controlling for other factors that may impact portfolio performance, the regression coefficient estimated for HHI is positive and significant (t-stat. = 5.002, $p < 0.01$). The results of the regressions also support the claim drawn from the statistics presented in Exhibit 2 that portfolios specialized in Communications and Electronics (Models 1 and 4), Internet and Computers (Models 2 and 3), Energy (Models 2 and 7), and Biotech and Healthcare (Models 2 and 8) have larger exit rates. Portfolios with higher levels of specialization in Business and Industrial (Models 2 and 5), Consumer (Models 2 and 6), Financial Services (Models 2 and 8), and Business Services (Models 2 and 4) are comparatively less successful, as revealed by the negative coefficients of the IIS variables.

To investigate whether VCs follow a strategy of investing in complementary new technologies, I further looked at investments in information technology in their portfolios. The analysis is based on the Herfindahl-Hirschman Index across the industry categories on the "software stack" proposed by Gao and Iyer [2006] (HHI.STACK). Portfolio exit rates were computed only for companies in the IT industries, since potential benefits from this type of strategy are likely to benefit mainly investments in information technology.

EXHIBIT 7

Regressions of Successful Exits on HHI and IIS Measures

Dependent variable is EXIT, defined as the fraction of the VC's portfolio companies that have been successfully exited via an IPO or M&A. CVC is a dummy variable equal to one if the VC is a corporate VC. IND.VC is a dummy variable equal to one if the VC is an independent VC firm. OVC is a dummy variable equal to one for all other types of VCs. EARLY.STAGE is a dummy variable equal to one if the company prefers to invest in early stages of development. NCOMP is the number of entrepreneurial companies in the portfolio. COMP.AGE is the average of the age of the companies in the portfolio, counted from the year of the first round of VC funding the company received. VC.AGE is the age of the VC firm in years. PROP.INT is the proportion of internet companies in the portfolio. HHI is the Herfindahl-Hirschman Index across the industry categories proposed by Gompers, Kovner, Lerner, and Scharfstein [2008]. IIS is the Index of Industry Specialization for each industry category.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	**–0.006**	**0.001**	**0.034**	**0.033**	**0.072**	**0.054**	**0.034**	**0.032**	**0.040**	**0.046**
	–0.374	*0.035*	*2.669****	*2.670****	*5.693****	*4.274****	*2.769****	*2.604****	*3.246****	*3.699****
log(NCOMP)	**0.017**	**0.011**	**0.012**	**0.012**	**0.011**	**0.012**	**0.012**	**0.012**	**0.012**	**0.012**
	*5.157****	*3.466****	*3.693****	*3.585****	*3.502****	*3.685****	*3.874****	*3.711****	*3.755****	*3.700****
CVC	**0.036**	**0.029**	**0.043**	**0.041**	**0.032**	**0.039**	**0.044**	**0.044**	**0.043**	**0.042**
	*3.483****	*2.856****	*4.214****	*4.032****	*3.151****	*3.821****	*4.393****	*4.409****	*4.288****	*4.179****
OVC	**–0.006**	**–0.006**	**–0.007**	**–0.007**	**–0.006**	**–0.008**	**–0.008**	**–0.008**	**–0.007**	**–0.008**
	–0.751	*–0.786*	*–0.967*	*–0.871*	*–0.796*	*–1.027*	*–0.988*	*–1.056*	*–0.954*	*–0.992*
EARLY.STG	**–0.049**	**–0.063**	**–0.045**	**–0.044**	**–0.056**	**–0.050**	**–0.041**	**–0.045**	**–0.043**	**–0.045**
	*–7.307****	*–9.135****	*–6.769****	*–6.833****	*–8.459****	*–7.481****	*–6.354****	*–6.925****	*–6.577****	*–6.850****
COMP.AGE	**0.062**	**0.059**	**0.062**	**0.061**	**0.059**	**0.061**	**0.062**	**0.062**	**0.062**	**0.061**
	*28.519****	*27.476****	*28.512****	*28.970****	*27.777****	*28.797****	*29.454****	*29.441****	*29.191****	*28.957****
VC.AGE	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**
	*2.799****	*2.871****	*2.463****	*2.615****	*3.278****	*2.820****	*2.350****	*2.346****	*2.549****	*2.564****
PROP.INT	**–0.026**	**–0.045**	**–0.043**							
	–1.657	*–2.247***	*–2.150*							
HHI	**0.081**									
	*5.002****									
IIS.IC		**0.030**	**0.014**							
		*2.22****	*2.557***							
IIS.CE		**0.017**		**0.009**						
		*2.52****		*3.192****						
IIS.BI		**–0.011**			**–0.022**					
		*–1.81***			*–8.469****					
IIS.C		**0.001**				**–0.011**				
		0.109				*–4.673****				
IIS.E		**0.004**					**0.003**			
		*4.143****					*3.498****			
IIS.BH		**0.012**						**0.006**		
		*2.718****						*4.131****		
IIS.FS		**0.003**							**–0.001**	
		0.932							*–0.692*	
IIS.BS										**–0.005**
										*–2.892***
R^2	24.00%	25.76%	23.64%	23.70%	24.87%	23.93%	23.74%	23.83%	23.51%	23.67%
F-stat.	155.9	97.8	152.9	175.3	186.8	177.5	175.7	176.6	173.5	175
N.Obs.	3959	3959	3959	3959	3959	3959	3959	3959	3959	3959

*Notes: t-statistics are reported below each coefficient in italic. The significance levels for the independent variables are given by: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.*

As shown in Exhibit 8, the results obtained for the sample of investments in information technology are in the opposite direction from the results based on the industry classification at the level proposed by Gompers et al. [2008], presented in Exhibit 7. I find evidence that portfolios diversified on the different layers of the "software stack" exhibit better performance. The coefficient of the variable HHI.STACK is insignificant for the regression on the entire sample (t-stat. = -0.417, p > 0.10) and on the subsample of VCs that invested more than 50 percent in companies in IT (t-stat. = -0.828), but becomes significant for the subsample of VCs with more than 75 percent of the companies in IT (t-stat. = -1.96, p < 0.10). The negative sign of the coefficient of HHI.STACK indicates that exit rates increase with lower degrees of specialization of the portfolio. Models 4 and

EXHIBIT 8

Regressions for the Subsample of Portfolios with Investments in Information Technology

Dependent variable is STACK.EXIT, defined as the fraction of the VC's portfolio companies in IT that have been successfully exited via an IPO or M&A. CVC is a dummy variable equal to one if the VC is a corporate VC. IND.VC is a dummy variable equal to one if the VC is an independent VC firm. OVC is a dummy variable equal to one for all other types of VCs. EARLY.STAGE is a dummy variable equal to one if the company prefers to invest in early stages of development. NCOMP is the number of entrepreneurial companies in the portfolio. COMP.AGE.S is the average of the age of the companies in IT in the portfolio, counted from the year of the first round of VC funding the company received. VC.AGE is the age of the VC firm in years. PROP.INT is the proportion of internet companies in the portfolio. HHI. STACK is the Herfindahl-Hirschman Index across industry categories constructed based on the "software stack" industry classification. Model 1 includes all portfolios with at least two companies in Information Technology. Model 2 includes portfolios where the proportion of companies in Information Technology is larger than 50%. Models 3, 4, and 5 include portfolios where the proportion of companies in Information Technology is larger than 75%.

	Model 1 All	**Model 2 Prop > 50%**	**Model 3 Prop > 75%**	**Model 4 Prop > 75%**	**Model 5 Prop > 75%**
Intercept	**0.025**	**0.026**	**0.027**	**0.030**	**–0.062**
	1.301	*1.132*	*0.947*	*0.742*	*–2.043*
CVC	**0.047**	**0.043**	**0.053**	**0.050**	**0.048**
	*3.882****	*3.414****	*3.850****	*3.627****	*3.507****
OVC	**–0.002**	**–0.001**	**–0.003**	**–0.004**	**–0.004**
	–0.211	*–0.058*	*–0.188*	*–0.274*	*–0.259*
EARLY.STG	**–0.038**	**–0.048**	**–0.042**	**–0.039**	**–0.038**
	*–4.650****	*–5.159****	*–3.837****	*–3.537****	*–3.481****
COMP.AGE.S	**0.230**	**0.246**	**0.252**	**0.255**	**0.246**
	*23.157****	*20.332****	*17.176****	*17.392****	*16.999****
VC.AGE	**0.002**	**0.002**	**0.003**	**0.003**	**0.003**
	*4.215****	*3.700****	*3.505****	*3.486****	*3.754****
PROP.INT	**–0.062**	**–0.088**	**–0.089**	**–0.110**	
	*–3.559****	*–4.756****	*–4.384****	*–3.445****	
HHI.STACK	**–0.008**	**–0.018**	**–0.048**		
	–0.417	*–0.828*	*–1.960**		
PROP.HARDWARE				**–0.027**	**0.062**
				–0.795	*2.778****
PROP.SYSTEMS				**0.043**	**0.130**
				0.823	*2.796****
PROP.MIDDLEWARE				**–0.030**	**0.061**
				–0.515	*1.170*
PROP.APPLICATIONS				**–0.065**	**0.016**
				*–1.699**	*0.542*
R^2	17.20%	18.45%	19.71%	19.80%	19.29%
F-stat.	106.8	88.11	64.67	45.46	48.9
N.Obs.	3653	2734	1852	1852	1852

*Notes: t-statistics are reported below each coefficient in italic. The significance levels for the independent variables are given by: *** = p < 0.01, ** = p < 0.05, * = p < 0.10.*

5 also suggest lower levels of performance for portfolios that focus on software applications, when compared with focus on other layers of the software stack, even after controlling for the proportion of investments in internet companies (variable PROP.INT). The coefficient of the variable PROP.APPLICATIONS is negative and significant in the regression presented in Model 4 (*t*-stat. = -1.699, p < 0.10).

CONCLUSION

This article studies the impact of VC portfolio industry strategy on portfolio performance. Three types of strategies are considered: industry specialization, industry diversification, and complementary networks investments. Consistent with previous work, I found that specialized portfolios perform better, as measured by a greater likelihood of profitable exit through IPO or M&A. I also find evidence that portfolios that focus on investment in information technology, energy, and biotech exhibit better performance. For the subsample of portfolios with investments in information technology, I found that diversification according to a narrower industry classification that entails the concept of "software stack" increases the rate of success of the portfolio. I consider that these investments may be complementary components of network systems and that value is created from this type of strategy.

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