Corporate Venture Capital: Stock Market Reactions and Impact on Investee Exit

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April 2, 2018

Abstract

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This study focuses on the impact of corporate venture capital (CVC) investments on the corporation's stock price and on the investee's exit probability. Event study results show no statistically significant stock market reaction to news of a CVC investment or an investee's exit, except when reactions to investments with or without strategic alignment are compared. In these cases, investments in startups in a different industry to the corporate parent elicit a negative abnormal return, and in startups in the same industry a positive abnormal return. While the stock market reactions studied are immediate, the study also aims to identify longer term effects of CVC investments on the investee's exit probability. Survival models built for this purpose identify investment characteristics including experience, funding size, co-investment, strategic alignment, and market conditions that positively and negatively affect exit probability. Notably, strategic alignment is found to lower exit probability. The paper discusses possible reasons for these findings, drawing on prior work, anecdotal evidence from CVC practitioners, and case studies for support.

I. Introduction

Corporate venture capital (CVC) is "the investment of corporate funds directly in external start-up companies" (Chesbrough, 2002). Over the last decade, corporations across industries have increased their presence in the venture capital space. Corporate funds made up 11% of total VC investment in 2011, a level unparalleled since the dot-com bubble (Lerner, 2013). Since then, the number of CVC groups globally has tripled (Himler, 2017). While some of this activity has been in line with broader institutional investment in the venture capital asset class as returns from traditional investments lag in the low interest rate environment, this is not the only driver. Companies are also looking to their venture arms as a source of innovation as global growth slows and internal R&D functions face cost-cutting pressures (The Boston Consulting Group, 2012) (Lerner, 2013).

This paper aims to determine first if these potential rewards from corporate venturing are reflected in the corporate's stock price, and second how the probability of success for the startup (with success defined as an exit) varies with different features of the investment. While the size of these investments is usually small relative to the investing company's balance sheet, the returns can be significant if they are successful. This is especially true if the investments are in companies with synergies that will help the investor's business grow, or in companies developing technologies that transform the industry. Given the upside potential, the expectation is that companies can derive significant value from CVC activity and that the stock market should reward this. Conversely, the startup gains from the corporate's industry knowledge, access to customers, and from the reputational benefits of association with a prominent marquee customer, which should make it more likely to achieve a successful exit. However, the degree to which the startup gains these advantages likely varies with characteristics of the CVC. Therefore, the study will aim to identify differences in the presence and magnitude of stock price impact and exit probability across various axes, including industry, investment stage, investment type (financial/strategic), maturity of the venture group, and nature of exit.

This area of research is significant for two reasons. First, it will support management decisions to initiate or continue CVC activity. Venture capital investors usually see many of their portfolio companies fail, but they are more than compensated for this by outsize returns from their top investments. Corporations are unwilling to accept this uncertainty and frequently pull out of venture investing after their first few failures, with the "median life span of corporate venturing programs hovering around one year" (Lerner, 2013). Evidence of positive stock price impact will help allay management's concerns about short-term losses and empower them to make venturing decisions for the longer term. On the flipside, it will also help shareholders recognize the value of venturing activity and be more patient when evaluating it.

II. Literature Review

Existing research on corporate venture capital has focused largely on factors determining success, the most critical of which is strategic alignment between the investor and investee (Gompers & Lerner, 2000). Chesbrough categorizes CVC investments into driving (advancing current business), enabling (complementing current business), emergent (exploring new businesses), and passive (providing financial returns only), and finds that companies can grow their current and future business through the first three types of investment (2002).

Lerner identifies six ways in which corporations can benefit from venture investing, namely through faster response times, a better view of competitive threats, easier disengagement from unfavorable investments, leverage advantages from co-investing with independent VC (IVC) firms, increased demand for the investor's products, and financial returns on exiting investments

(Lerner, 2013). Using corporate venture funds to harness new technologies has been found to increase firm value as measured by 'Tobin's q' (market value less tangible assets), which is a proxy for competitive advantage (Dushnitsky & Lenox, 2006). Startups backed by corporate venture funds also see benefits, achieving higher market returns and revenue growth after going public than companies backed by independent VC firms (Chemmanur, Loutskina, & Tian, 2014). This paper, conversely, studies how the CVC's investment process affects the likelihood of going public or achieving exit, rather than post-IPO performance.

Finally, there is extensive research on the impact of M&A activity on stock prices, but this is vastly different from venture investments given the small size, early stage, and innovation potential of the latter. This paper focuses specifically on the stock price impact of venture investments, which is not well researched, and will bridge the gap between success in corporate venturing and success in the stock market.

III. Data and Methodology

III.1 Data

This paper focuses on venture capital activity by CVC groups in the United States. Data on the groups themselves as well as their investments is drawn from CB Insights. This is supplemented with market capitalization data on the CVC parents from the Center for Research in Security Prices (CRSP) and from S&P Capital IQ (CapIQ), as well as market data from S&P NetAdvantage and Thomson ONE Banker. The data is described in greater detail in the following sections.

III.1.i CVC Groups

CB Insights identifies 337 corporate venture investors in the United States. For each investor, it provides a description, location, and the number of investments and exits.

Investor	Investor Description	Inv. URL	# Deals	# Exits	Investor Type	Inv. Country	Inv. State	Inv. City
Intel Capital	Intel Capital, is a global investing organization t...	intelcapital.com	1649	N/A	Corporate Venture	United States	California	Santa Clara
Google Ventures	GV (Google Ventures) seeks to discover and in...	gv.com	585	N/A	Corporate Venture	United States	California	Mountain View
Qualcomm Ventures	Qualcomm Ventures (QCV) was formed and be...	qualcommve...	501	N/A	Corporate Venture	United States	California	San Diego
Salesforce Ventures	Salesforce Ventures-Salesforce's corporate inv...	salesforce.com	282	N/A	Corporate Venture	United States	California	San Francisco
In-Q-Tel	In-Q-Tel identifies and partners with companies ...	iqt.org	266	N/A	Corporate Venture	United States	Virginia	Arlington

Figure 1: Screenshot of CB Insights search results for corporate venture investors located in the United States

From this list of investors, 50 CVC groups were randomly sampled for analysis (Appendix 1 – List of 50 CVC Groups), which have together invested in a total of 1,919 companies between December 1995 and October 2017. Over the same time period, 714 of these investments had successful exits.

III.1.ii Investments and Exits

For each of the 50 CVCs, additional information was obtained from CB Insights on the specific investment and exit events, as outlined in Table 1.

Investments	Exits
Investment date	Exit date
Investee	Investee
Size of funding round	Valuation at exit
Round	Type of exit
Co-Investors	Acquirer
New vs. follow-on	Press mentions
Press mentions	

Table 1: Investment and exit information drawn from CB Insights

III.1.iii Parent Corporations

Market capitalization data for the CVC groups' parent corporations was drawn from CRSP for dates through December 31, 2016, at which point that dataset ends, and from Capital IQ thereafter.

III.1.iv Market Data

Two categories of market data were used. The first is equity market indicators such as levels and growth rates of the S&P 500 and NASDAQ indices drawn from S&P NetAdvantage, and the second is VC funding data drawn from Thomson ONE Banker. The latter included both the aggregate funding raised each month, as well as a measure of capital overhang calculated from the funds available after investment. Capital overhang or 'dry powder' refers to the amount of capital that has been raised by a fund that has not yet been deployed. In other words, it is the difference between committed and invested capital. A high level of capital overhang in the market can be problematic, since it "could amplify competition between funds, raise transaction values and ultimately challenge returns" (Cambridge Associates, 2014). The calculation methodology is described in Appendix 3 – Capital Overhang Calculation.

III.2 Methodology

III.2.i Event Studies

The first approach used to determine the impact of corporate venture investments and exits on the parent's stock price is the use of event studies. Event studies are a widely used tool in finance and economics to determine the behavior of a firm's stock prices around corporate events. Applications include determining how shareholders have benefited from corporate decisions, testing for market efficiency, and assessing damages in legal liability cases (Kothari & Warner, 2004). Event studies are perhaps most commonly used to study the effects of earning announcements or mergers and acquisitions.

The first step in conducting an event study is to define an event of interest, which for this paper is either an investment or an exit by a CVC group, and the event window – a period of time over which the stock price is to be monitored. This period usually ranges from a few days before to a few days after the event, since news of the event can leak prematurely, or market participants can take time to respond to new information. The next step is to select a measure of abnormal returns. This is done by specifying a model of expected returns and measuring the actual return above what the model predicts over the event window. For firm i on day t, the abnormal return may be defined as shown in Equation (1). The Cumulative Abnormal Return (CAR) defined in

Equation (2) is the abnormal return for firm *i* over the entire event window, and the mean CAR is the average measure for all the firms under consideration.

$$AR_{it} = R_{it} - E(R_{it}) \tag{1}$$

$$CAR_i = \sum\nolimits_{t=start}^{end} AR_{it} \tag{2}$$

$$\overline{CAR} = \frac{1}{N}\sum\nolimits_{i=1}^{N} CAR_i \tag{3}$$

The expected return can be calculated using statistical models, with mean returns, market model, three factor, and three factor with momentum models being the common ones, or using economic models like the Capital Asset Pricing Model and the Arbitrage Pricing Theory. The economic models have biases which the statistical models overcome, and the factor models provide limited gains over the mean and market models (MacKinlay, 1997). However, all the models require a market portfolio, which is usually approximated by a broad-based stock index like the S&P 500 or the CRSP Equal Weighted or Value Weighted Index. The expected return model is estimated over a period that is separated from the event window by a gap to prevent biasing the model results. The timeline in Figure 2 shows the different windows.

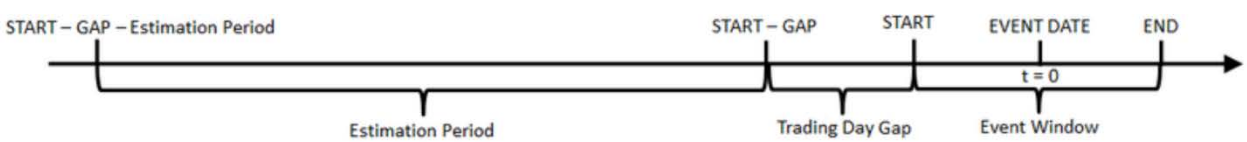

Figure 2: Event study timeline (The Wharton School, University of Pennsylvania, n.d.)

The final step in the event study process is to test the null hypothesis of zero abnormal returns using a normal distribution for the mean cumulative abnormal return.

$$\overline{CAR} \sim N\left(0, var(\overline{CAR})\right) \tag{4}$$

The event studies in this paper were performed using the U.S. Daily Event Study web application available from Wharton Research Data Services (WRDS) which follows the process outlined above.

III.2.ii Survival Analysis

Survival analysis is a statistical approach to analyze the duration of time until an event happens, such as death in a biological organism or failure in an engineering system. Data in such studies have three characteristics: (i) the dependent variable is the waiting time till the event, (ii) observations are censored, so that the event may not have happened over the observation period, and (iii) there are explanatory variables which affect the waiting time (Rodríguez, 2007). For the purposes of this study, the primary event under study is a successful exit from an investment, and the survival time is the time between the initial investment and the exit date. Observations are censored since all investments will not have exited by the end of the observation period. Actually, many investments were likely written off before the end of the observation period, which could be classified as another type of event. Follow-on investments could also similarly be classified as different types of events, but the analysis is done focusing only on the initial investment and final exit events. The purpose of this analysis is to determine which explanatory variables, i.e. which features of the investor, investee, or investment have an impact on the time till exit.

The setup for the analysis begins by defining a random variable T which denotes the time of the event happening. Then, a survival function is defined which describes the probability of surviving till time t:

$$S(t) = P\{T \geq t\} = 1 - F(t) = \int_t^\infty f(x)dx \qquad (5)$$

Alternatively, the hazard function is defined which is the instantaneous rate of occurrence of the event:

$$\lambda(t) = \lim_{dt \to 0} \frac{P\{t \le T < t + dt | T \ge t\}}{dt} = \frac{f(t)}{S(t)} \tag{6}$$

Models to describe survival times or hazard as a function of covariates can take many forms, but the Cox proportional hazards model is commonly used because of its ability to closely approximate the results from the correct parametric model (Kleinbaum & Klein, 2005). This means that the model can be used to yield robust results even if the distribution of the variables is not known. The Cox model directly describes the hazard rate as a product of a baseline hazard and an exponential function of a set of covariates as shown in Equation (7), where *i* refers to an individual investment, $\boldsymbol{x_i}$ is a vector of covariates, and $\boldsymbol{\beta}$ are the coefficients.

$$\lambda_i(t, \boldsymbol{x_i}) = \lambda_0(t)\exp\{\boldsymbol{x_i'\beta}\} \tag{7}$$

Another advantage of the Cox model is that the coefficients can be obtained even if the baseline hazard is not specified, which makes it possible to compare the relative effects of the different covariates. The proportional hazards model can also be extended to accommodate time-varying covariates, to account for effects that vary over the course of the observation window rather than just those that occur at the start or the end points:

$$\lambda_i\big(t, \boldsymbol{x_i}(t)\big) = \lambda_0(t)\exp\{\boldsymbol{x_i}(t)'\boldsymbol{\beta}\} \tag{8}$$

For these time-varying covariates, the variable is sampled at the investment and exit date, as well as at every month-end in between those two dates. This means, for example, that an observation for an investment on December 15, 2015 which has an IPO on January 20, 2017, is converted into 14 observations. The first observation starts on December 15 and ends on December 31, 2015. The second starts on January 1, 2016 and ends on January 31, the third starts on February

1 and ends on February 29, and so on. The last observation starts on January 1, 2017 and ends on January 20, and is the only observation that has an exit indicator.

Survival models were built using the survival package in the R statistical programming software.

IV. Results

IV.1 Event Studies

Event studies were conducted across a range of windows around the investment and exit dates. In all cases, the Fama-French plus Momentum model was used with the CRSP Value-Weighted Index as the market portfolio. The estimation window was set to 100 days with a minimum of 70 valid returns required over the period. A gap of 50 days separated the estimation and event windows. Investments were grouped by a number of characteristic features and mean CARs and test statistics were computed for each group.

Taking all investments together, the mean CARs ranged from -0.10% to 0.01% over different event windows, as shown in Table 2, but lacked significance across all the windows. Mean CARs around exit events ranged from 0.02% to 0.16% but these too were not significant.

Event Window[1]	**Investment Event**[2]			**Exit Event**[3]		
	Mean CAR	t-stat	p-value	Mean CAR	t-stat	p-value
(0, 1)	-0.04%	-0.71	0.48	0.08%	0.74	0.46
(0, 3)	0.00%	-0.02	0.99	0.10%	0.70	0.48
(0, 5)	0.01%	0.11	0.91	0.04%	0.20	0.84
(-1, 1)	-0.10%	-1.43	0.15	0.05%	0.35	0.73
(-3, 3)	-0.03%	-0.26	0.80	0.16%	0.79	0.43
(-5, 5)	0.01%	0.10	0.92	0.02%	0.10	0.92

Table 2: Mean CARs for all investments and exits

[1] Event windows refer to days before and after the event at day 0. For example, (-1,1) denotes the period from one day before the event to one day after

[2] 2493 out 2816 investments (new and follow on) used for CAR calculation. Multiple investments by the same CVC on the same day are treated as separate events with identical CARs

[3] 628 out of 726 exits used for CAR calculation. There are a total of 726 exits here as opposed to 714 indicated earlier since CB Insights does not have investment records for the remaining 12 companies

Groupings of the investments across different dimensions also yielded few significant results. Some groupings considered for both investments and exits, along with results for the (-1, 1) window, are highlighted in Table 3 and Table 4. Certain results for mean CARs around the investment event are significant and are denoted by asterisks. For the ‘number of prior investments’ grouping scheme, the group closest to significance is the one for 6-10 prior investments. The negative abnormal return for the 6-10 group, assuming this result is causal and not just coincident, indicates that such limited experience is not sufficient to arouse market approval for CVC activity. This is reasonable given the fact that 75% of startups fail and even the ones that don’t fail take years to become profitable (Gage, 2012).

The second set of significant results is for the first three funding quintiles, with the first two showing negative CARs and the last showing a positive CAR but lower significance. If this trend is representative, there are two possible explanations for it. The first is that investors will exercise greater scrutiny if they are putting in more money, but this hypothesis is not borne out by the lack of directionality and significance in the event study results for investments segmented by funding size relative to the corporate’s market capitalization. The second explanation is that a large round size indicates the participation of many or more sophisticated co-investors who provide external validation for the investment, which is supported by the significant negative mean CAR for the group with no top-25 IVC co-investors. Additionally, the mean CAR for the Series A investments group is significant and also negative, perhaps because early investments are more ambiguous and therefore riskier.

The final set of segmentations was by the presence of a sector or industry match between the investee and the CVC groups parent corporation. Investments where there was no sector match showed a negative CAR while those where there was a sector match showed a positive CAR, though only the former was significant. When looking at industry matches however, CARs for both the presence and absence of a match were significant, with a negative CAR in cases of no match and a positive CAR when there was a match. While the industry match study is run only on half of the CVC groups whose parent corporations are assigned an industry classification by CB Insights, the results are still powerful since they are supported by the existing literature on strategic alignment between the investor and investee being a critical driver of success for CVC investing (Gompers & Lerner, 2000). CARs around exit events show the same directionality for sector and industry matches, though those results are largely not statistically significant.

Grouping Scheme	Group	Number of Investments	Number of Investments for CAR Calculation	Mean CAR (-1, 1)	t-stat	p-value
Number of Prior Investments	0-5	240	190	0.00%	0.00	1.00
	6-10	127	107	-0.62%	-1.41	0.16
	11-20	153	133	-0.32%	-1.01	0.31
	21-50	274	249	0.19%	0.68	0.49
	>50	2,022	1,814	-0.11%	-1.32	0.19
Funding Quintile[4]	1 (<=$5.4M)	469	427	-0.26%	-1.88	0.06**
	2 (<=$10M)	476	414	-0.33%	-1.72	0.08**
	3 (<=$16.5M)	466	421	0.25%	1.48	0.14*
	4 (<=$29.4M)	474	426	-0.07%	-0.34	0.74
	5 (<=$3.2B)	473	397	-0.18%	-0.87	0.39
Funding Relative to Market Capitalization[5]	0-0.01%	1,035	940	-0.20%	-1.69	0.09**
	0.01%-0.02%	517	469	-0.04%	-0.23	0.82
	0.02%-0.03%	217	183	-0.10%	-0.44	0.66
	0.03%-0.04%	140	125	0.25%	0.64	0.52
	>0.04%	428	368	-0.14%	-0.58	0.56
Number of Co-Investors	0	470	420	-0.08%	-0.63	0.53
	>0	2,346	2,073	-0.11%	-1.30	0.19
Number of Top-25 Co-Investors[6]	0	2,033	1,795	-0.14%	-1.61	0.11*
	>0	783	698	-0.03%	-0.17	0.86
New vs Follow-On	New	1,919	1,707	-0.12%	-1.33	0.18
	Follow-On	897	786	-0.08%	-0.59	0.55
Round	Seed	181	160	0.22%	1.18	0.24
	Series A	469	406	-0.25%	-1.57	0.12*
	Series B	688	613	0.10%	0.60	0.55
	Series C	499	449	-0.04%	-0.24	0.81
	Series D	257	222	0.26%	1.23	0.22
	Series E	114	100	-0.26%	-0.82	0.41

[4] Quintiles of the size of the funding round the CVC participated in
[5] Size of the funding round the CVC participated in relative to the CVC group's parent's market capitalization
[6] IVCs with the most number of deals (listed in Appendix 2 – List of Top-25 Independent Venture Capital Firms)

Grouping Scheme	Group	Number of Investments	Number of Investments for CAR Calculation	Mean CAR (-1, 1)	t-stat	p-value
	Series F/G/H	32	27	-0.08%	-0.17	0.86
Sector Match[7]	No Match	2,198	1,950	-0.14%	-1.73	0.08**
	Match	618	543	0.03%	0.16	0.87
Industry Match[8]	No Match	1,672	1,516	-0.19%	-1.93	0.05***
	Match	217	199	0.44%	1.55	0.12*

Table 3: Mean CARs through the (-1, 1) event window around investment dates

Grouping Scheme	Group	Number of Investments	Number of Investments for CAR Calculation	Mean CAR	t-stat	p-value
Valuation Quintile (at exit)	1 (<=$23M)	76	71	-0.05%	-0.09	0.93
	2 (<=$77M)	75	63	0.24%	0.60	0.55
	3 (<=$171M)	75	70	0.11%	0.32	0.75
	4 (<=$367M)	75	61	-0.53%	-1.39	0.16
	5 (<=$52B)	76	70	0.07%	0.14	0.88
Type of Exit	Acquired	627	546	0.03%	0.20	0.84
	IPO	53	47	0.18%	0.56	0.58
	Other[9]	46	35	0.12%	0.29	0.77
Sector Match	No Match	596	522	0.01%	0.20	0.84
	Match	130	106	-0.03%	-0.08	0.93
Industry Match	No Match	455	398	0.01%	0.14	0.89
	Match	53	43	0.80%	1.45	0.15*

Table 4: Mean CARs through the (-1, 1) event window around exit dates

IV.2 Survival Analysis

Survival analysis was conducted by developing Cox proportional hazard models using different combinations of predictor variables with the intention of determining the relative effects of different predictors on the probability of a successful exit. Table 5 shows the regression coefficients and fit statistics for univariate regressions, while Table 6 shows survival plots for some of the univariate models for two values of the predictor variables. The results show that the probability of success increases as the total size of the funding round increases on an absolute or relative basis, and with the presence of co-investors (both in the top-25 IVC set as well as any co-investors at all). This is reasonable, since a large funding round and the presence of co-investors

[7] Match between the investors and investees sector as defined by CB Insights (CB Insights does not provide sector classifications for 25 of the 50 CVC groups parents and sectors for these are assigned by the author)
[8] Match between the investors and investees industry as defined by CB Insights (CB Insights does not provide industry classifications for 25 of the 50 CVC groups parents and investments by these groups are excluded)
[9] Other includes asset sale, corporate majority, management buyout, merger, and reverse merger

are an external validation of the startup's probability of success. The coefficient in the regression with the variable for the log of the number of prior investments, however, is negative, indicating that the probability of success decreases if the CVC group has made a lot of prior investments. One hypothesis is that a CVC group should become better at making investments as it gets more experience, so the probability of success should increase, and the coefficient should be positive. On the other hand, it is also possible that a more experienced CVC will be willing to take riskier bets, potentially lowering the exit probability. The negative coefficient suggests that this effect is stronger.

The coefficients in the regressions for sector and industry match are both negative, though only the sector match result is significant. This is a surprising result since it is in opposition to both the existing literature on factors affecting corporate venture success, and the event study findings in this paper which report a positive stock price impact when there is a match and a negative impact when there is no match. The first contradiction can likely be explained by methodological differences. Gompers and Lerner's paper on the determinants of corporate venture capital success, for example, defines strategic alignment as "a direct relation between a line of business of the corporate parent and the portfolio firm" as determined from an examination of the corporate's annual report from the year closest to the investment date (2000). In contrast, this paper defines strategic alignment as an exact match in the sector or industry classification assigned by CB Insights, with missing classifications supplemented by the author. The second contradiction, with the results of the event study, may be explained by the difference in the success measure. It is possible that stock prices rise when a corporate invests in a company in the same sector or industry because investors anticipate value creation through access to new technologies, customers, markets, or employees, but this value is not contingent on the company achieving a successful exit.

The final set of variables are time-varying and include levels and changes in market metrics such as the NASDAQ Composite Index, funding raised across the entire US venture capital industry, and US VC capital overhang. Of these, the only significant variable is monthly percent change in capital overhang. While high overhang levels can be problematic for investors, the positive coefficient here indicates that VCs are better able to add value and guide their investees to exit at such times (when other investment opportunities are limited) since they have fewer distractions.

Variable	Coefficient	Exp (Coefficient)	SE (Coefficient)	Z (Wald Statistic)	Pr (>|Z|)	p-value for Likelihood Ratio Test
Ln (Number of Prior Investments)	-0.033	0.968	0.020	-1.633	0.102	0.105*
Ln (Total Funding Raised in Round)	0.059	1.060	0.036	1.602	0.109	0.106*
Ln(Funding Relative to Market Capitalization)	0.085	1.089	0.028	3.038	0.002	0.003***
Number of Co-Investors > 0	0.638	1.894	0.117	5.466	0.000	0.000***
Number of Top-25 Co-Investors > 0	0.348	1.416	0.081	4.316	0.000	0.000***
Sector Match	-0.198	0.821	0.097	-2.033	0.042	0.038***
Industry Match	-0.176	0.838	0.145	-1.213	0.225	0.214
MoM Change in NASDAQ Composite Index	-0.649	0.522	0.798	-0.814	0.416	0.418
MoM Change in VC Funds Raised	-0.001	0.999	0.009	-0.084	0.933	0.933
Capital Overhang	-0.000	1.000	0.000	-0.7	0.484	0.483
MoM Change in Capital Overhang	1.887	6.600	1.097	1.72	0.085	0.085**

Table 5: Regression results for univariate proportional hazard models

The charts below show survival plots for some of the univariate hazard models discussed above. The survival plots show the probability of *NOT* exiting (equal to 1 minus the probability of exiting) as time from initial investment increases. Each plot has two lines for two different values of the covariate. An increase in the value of a covariate with a negative coefficient in the regressions above will lower the exit probability, so the line corresponding to the high-value of the covariate will be above the line corresponding to the low-value of the covariate.

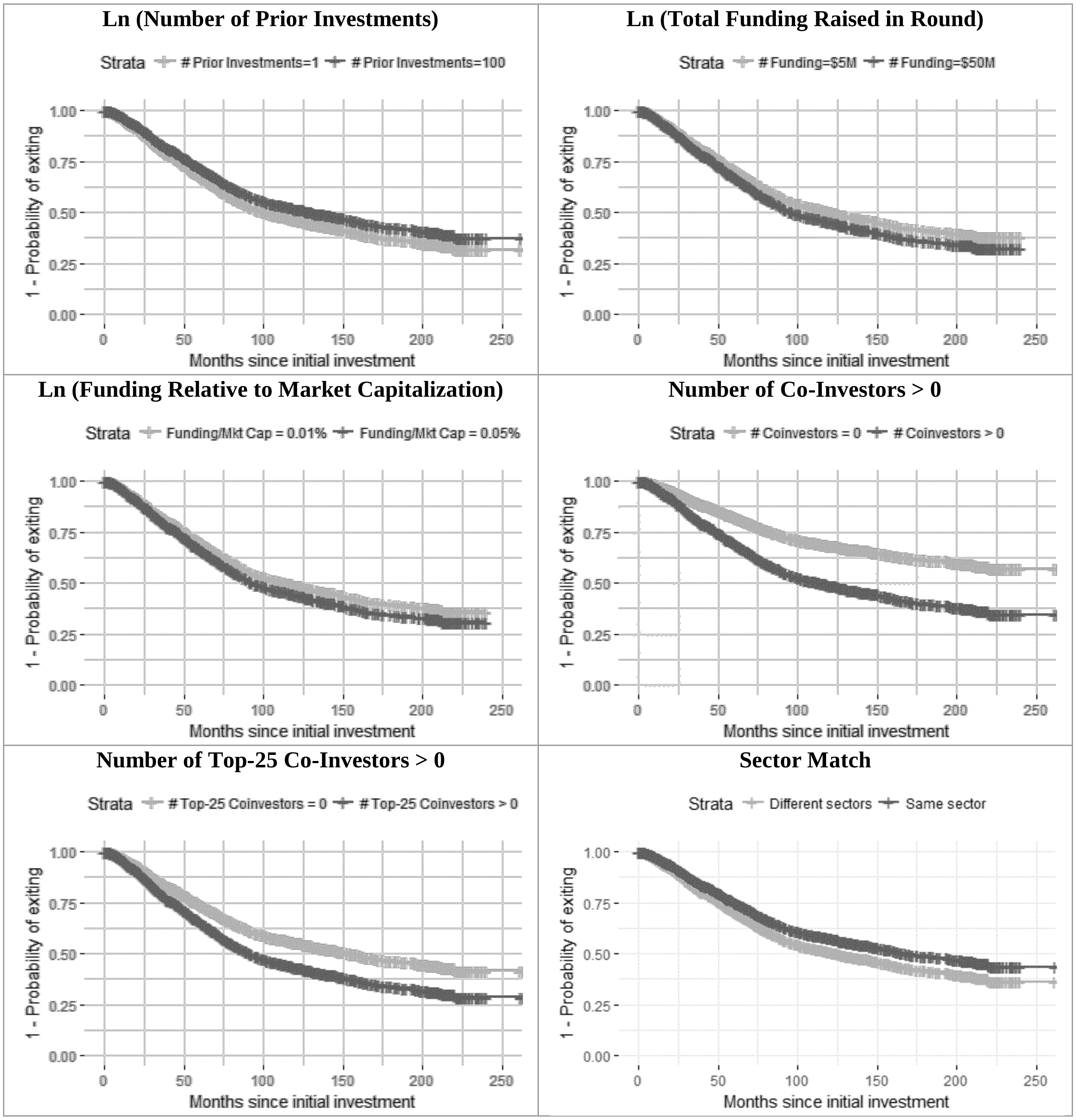

Table 6: Survival plots for univariate regressions showing two values of the predictor variable

For a multivariate regression including the significant variables from Table 5 above, all but two of the variables remain significant at a 10% significance level. The sector match variable stays significant at a 15% level and the indicator variable for the presence of a co-investor loses significance. The signs of two of the coefficients change as well. The coefficient for the log of the number of prior investments becomes positive, indicating that prior investment experience does help CVCs better pick winners. This contrasts with the univariate case where the coefficient indicated that exit probability decreased as investment experience increased. The variable for the log of absolute funding size becomes negative, even though the log of relative funding size retains its positive coefficient. The relative funding variable, however, has much higher statistical significance. The model overall is significant, and suggests that exit probability increases with investment experience, funding size relative to the corporate's market capitalization, the presence of a top IVC co-investor, and a dearth of venture investment opportunities.

Variable	Coefficient	Exp (Coefficient)	SE (Coefficient)	Z (Wald Statistic)	Pr (>|Z|)	p-value for Likelihood Ratio Test
Ln (Number of Prior Investments)	0.046	1.047	0.028	1.666	0.096**	0.007***
Ln (Total Funding Raised in Round)	-0.084	0.920	0.050	-1.665	0.096**	
Ln(Funding Relative to Market Capitalization)	0.114	1.121	0.043	2.631	0.009***	
Number of Co-Investors > 0	0.151	1.163	0.181	0.834	0.404	
Number of Top-25 Co-Investors > 0	0.177	1.194	0.085	2.094	0.036***	
Sector Match	-0.148	0.862	0.102	-1.458	0.145*	
MoM Change in Capital Overhang	2.194	8.973	1.161	1.890	0.059**	

Table 7: Multivariate regression results

V. Discussion of Analytical Results

The results obtained so far suggest that the stock market rewards or punishes CVC activity primarily based on whether it aligns with the corporate's core business, which agrees with the literature identifying strategic alignment as a key success driver. However, this alignment, at least as defined in this paper, actually harms the startup by lowering its chances of an IPO or acquisition. The factors that are beneficial to a successful exit are investor experience, relatively material investment sizes, co-investment by a top-25 IVC, and market conditions. This section expands on some of these findings using additional literature and commentary from CVC practitioners obtained from personal interviews and panel discussions.

The event study results show that the stock market overall does not react to news about venture investments or exits. This is likely a consequence of the small size of such investments. First, CVCs almost always restrict their stake in a startup to under 20% to avoid reporting under the equity method of accounting. In practice, the stakes are likely even lower given the presence of co-investors. Additionally, even if the stake acquired is substantial, it is often insufficiently "material to a large firm's results of operations, cash flows, or financial position" to warrant disclosure and frequently goes unreported by the parent corporation. In fact, such investments tend to be reported by the startups themselves through "industry trade publications, company press releases, websites, and social media" (Hamm, Jung, & Park, 2018). Given the lack of information, it is not surprising that the stock market response is minimal.

CVC investment experience, though not a significant driver of stock market returns, does correlate positively with the startup investee's exit probability. There are two factors that play into this. The first is the more obvious one relating to greater expertise developed through experience. In a personal interview, one practitioner from a top CVC explained that the post-investment monitoring process yields an understanding of what products, technology architectures, and business models are most aligned to the corporate's operations. The startups that have the most complementary features are generally the ones with whom the mutual benefits are the greatest, and experience helps identify these complementarities. The second factor is the corporate's belief in the CVC. Practitioners at a recent New York University (NYU) panel agreed that corporates are often cautious with new CVC groups, especially since losses can manifest before wins. This may translate into less autonomy given to the CVC group in its infancy and therefore lower performance. The mandate given to the CVC may also evolve over time. For example, Rumi Morales, the executive director of CME Ventures, describes how their investment focus narrowed over the first eighteen months from any technology that impacted their current business to five specific technology areas (MacArthur, 2015). Such an evolution will have an impact on investment selection and therefore on exit probability.

Perhaps the most important analytical finding from this report is the impact of strategic alignment in an investment – positive for the corporate's stock price, but negative for the startup's exit probability. The stock price impact is notable because industry alignment is one of the few dimensions along which we see a statistically significant abnormal return. One CVC practitioner explained the overall lack of a stock market response by saying that the deals his group made were too small relative to the corporate to move the needle financially in the short term, but he did note the possibility of the market responding positively if it was already concerned about a competitive threat and they made an investment which addressed that threat. The investment need not be reactive to elicit a response. A few practitioners talked about how corporates were increasingly outsourcing innovation to outside ventures, using CVC to shift into services that the corporate had struggled to expand into internally, or to fill specific needs identified by business unit leaders. The long-term strategic benefits from such investments would likely be recognized and rewarded by the stock market as well.

The negative impact of sector alignment on the startup's exit probability is suggestive of the dark side of CVC investing. While startups do benefit from the corporate's industry expertise and access to partnership opportunities, there is a recognized risk of "misappropriation of their technology by corporate investors," which some investees avoid by limiting the corporate investor's access and stake (Ewing Marion Kauffman Foundation, 2016). This concern must be addressed by the CVC as well, with one practitioner describing a gradual trust-building process that assures the startup that the CVC will not leak confidential information or trade secrets to the corporate parent. Such trust-building depends on reputation but can also include practices like complete separation of the investment agreement from any commercial agreements that the startup may have with the corporate. While some CVC groups put such measures in place to protect the startup, Dushnitsky and Lenox find evidence for appropriation in the form of increases in corporate patents following periods of increased CVC investing, especially in weak intellectual property (IP) regimes (2006). Of course, it is possible that strategic investments do not cause but are coincident with lower exit probabilities. Since strategic investors gain non-financial value from their portfolio companies even in the absence of an exit, they may be selecting their investments to maximize either this non-financial return on its own, or the sum of financial and non-financial returns. As a result, the expected financial return (as achieved through an exit) is lower for a strategic portfolio than it would be for a financially-oriented portfolio. This is supported by anecdotal evidence from a practitioner from one mixed objective CVC group which evaluates prospective investments for strategic potential when their financials are weak, and for financial potential when they are unlikely to provide much strategic value. In any case, it is clear that startups seeking strategic investments need to implement adequate IP protections, and CVC groups need an unambiguous investment objective to ensure they get what they pay for.

VI. Case Study of Selected CVC Groups

The analysis so far identifies factors impacting stock market returns and exit probabilities across the sample of fifty US CVCs. This section dives into some of these factors through two comparative case studies. To ensure that the comparisons are useful, each pair of CVCs is selected so that the CVCs have at least some features in common. Investment period is one such feature where consistency is important. If the observation window beginning in 1995 (when the first investment in the sample was made) is split up into five-year periods, Figure 3 shows that companies that received their first investment from a particular CVC in later periods had a lower fraction of their cohort exiting. This is partly because there is less time left to exit for a company receiving a later investment, but also because exit probabilities for startups change over time due to economic conditions. This is the reason why VC and PE funds are benchmarked based on their vintage year. Additionally, CVC groups are chosen for the case study so that they have made investments in at least ten companies over their comparison window, each CVC in a pair made a similar number of investments over that window, and their corporate parents are in similar industries.

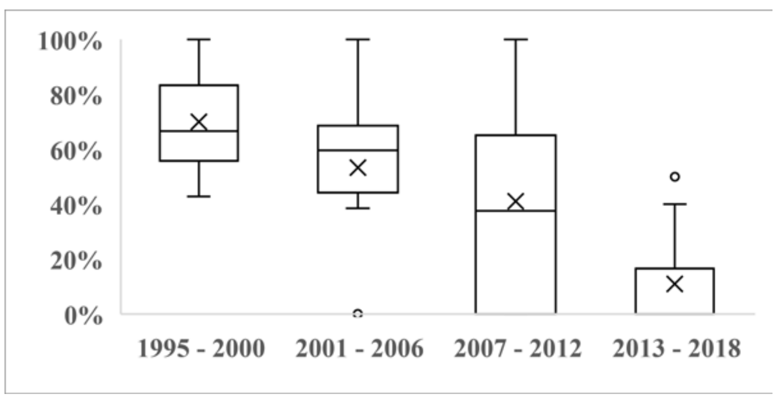

Figure 3: Fraction of investments made by CVC sample set in five-year periods that achieved subsequent exit

The first comparison is between Maxim Ventures and SanDisk Ventures, both of which are relatively new, have been active over the same period, have made the same number of investments over the observation period, and have parent corporations in the same sector, but have a large difference in the fraction of their investments that have exited. For Maxim and SanDisk, the observation window begins in December 2012 when SanDisk made its first investment and continues through October 2017. SanDisk was acquired by Western Digital in May 2016, and only pre-acquisition investments made by SanDisk Ventures are included in this comparison, though exits are allowed to be post-acquisition.

The second comparison is between Time Warner Investments and AOL Ventures, with the observation window beginning in December 2009 right after AOL was spun off from Time Warner and AOL Ventures made its first investment, and ending in December 2014. Over this five-year period, both groups made a similar number of investments, but Time Warner has seen a larger fraction of those investments achieve subsequent exit. A key strength of this comparison is that Time Warner and AOL had a lot in common due to their nine-year merger. While the merger itself has been called the "worst deal in history," integration of the two organizations at the corporate level and their complementary aims – digitization and online distribution for Time Warner and content for AOL – means that comparing them in the period immediately post-demerger minimizes confounding effects (Quinn, 2009).

VI.1 Maxim Ventures and SanDisk Ventures

CVC Group	Parent Corporation	Corporate Sector	Date of First Investment	New Investments in Observation Window[10]	Number of Exits	Fraction Exited
Maxim Ventures	Maxim Integrated Products	Electronics	2/6/2013	11	0	0%
SanDisk Ventures	SanDisk Corporation	Electronics	12/13/2012	11	5	45%

Table 8: Summary Information for Maxim Ventures and SanDisk Ventures

Maxim Ventures is the venture arm of Maxim Integrated Products, a semiconductor company which develops integrated circuits for a wide range of applications. Maxim Ventures describes its objective as "investing beyond the chip … to create new revenue streams beyond semiconductors and from system, software, and service businesses." Specifically, it aims to bridge the gap between data measurement and analysis using chips, sensors, and algorithms in order to

[10] December 2012 – October 2017

capture the higher end of the analytics value chain which comprises data driven insights and decisions. Maxim claims to provide value in the form of technology, relationships, and funding to its investees, and in return, hopes to gain increased chip sales, information on use cases and market trends, and ways to capture more "data value" (Maxim Ventures, 2015).

SanDisk Ventures is the venture arm of SanDisk Corporation, a leading producer of flash memory data storage products. SanDisk Ventures was formed with the goals of accelerating market growth, providing insights into flash use cases, and improving industry relationships particularly in the enterprise storage segment (BusinessWire, 2012). During SanDisk's 2013 Investor Day, Chief Strategy Officer Sumit Sadana emphasized the expansion of flash use cases as an important part of the strategy behind SanDisk Ventures (SanDisk, 2013).

Perhaps the biggest driver of the difference in exit fractions is SanDisk's tendency to invest in later stage companies than Maxim as shown in Figure 4. With the median time from initial VC financing to IPO hovering around seven years in 2012-13, it is not surprising that early stage investments made after this period haven't exited yet (Wilmer Hale, 2015). However, as discussed below, this is not the only reason.

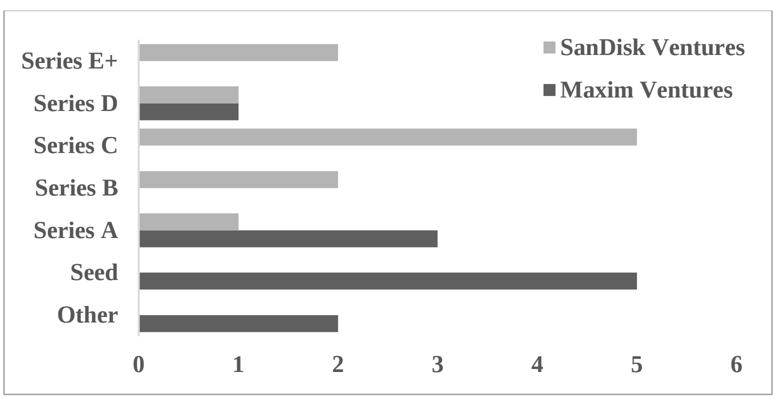

Figure 4: Number of Initial Investments by Stage

The difference in objectives between Maxim and SanDisk suggests another possible reason for the difference in exit ratios. While SanDisk focused on market growth through expanded use cases of its products, Maxim is trying to use its startup partners as a source of new lines of recurring revenue, perhaps through closer and more controlled partnerships with its investees that may restrict or slow down their growth. On the other hand, SanDisk's approach suggests that they want their investees to grow rapidly and become large customers of their products, and therefore have a greater incentive to encourage exit. In line with these objectives, SanDisk's investees operate in several industries including hardware, software, internet, mobile and telecom, industrial products, and electronics to maximize market growth, while Maxim's investments are more concentrated with most being in healthcare or consumer products to capture value through verticals.

Next, size differences are also likely to play a role. Though Maxim had a larger pool of capital to deploy with a $200 million fund as opposed to SanDisk's $75 million commitment over its first three years, the deals that Maxim participated in were much smaller both in absolute terms and relative to Maxim Integrated's market capitalization (Table 9). This is at least partly a consequence of the stages that the two groups invest in, since later stage valuations tend to be higher. However, it does align with the analytical finding that a higher relative funding size correlates with higher exit probability.

CVC Group	**Size of Funding Round**		**Market Capitalization at Investment**		**Funding Size Relative to Market Capitalization**	
	Average	**Median**	**Average**	**Median**	**Average**	**Median**
Maxim Ventures	$11.3M	$5.1M	$10.0B	$9.5B	0.12%	0.05%
SanDisk Ventures	$23.4M	$26.0M	$15.9B	$15.7B	0.16%	0.16%

Table 9: Deal Sizes for Maxim Ventures and SanDisk Ventures[11]

Finally, and perhaps also because of the difference in stages, SanDisk had co-investors more often and in greater numbers than Maxim did, and also had a top-25 IVC co-investor in four deals while Maxim has yet to co-invest with a top-25 IVC. In addition to the preference for investing in later rounds, it is possible that top-25 IVCs stay away from Maxim's deals based on

[11] Including both new and follow-on investments

their investees' poor exit history. Comparing these two CVCs reveals that their investees have very different exit track records. While this is largely explained by the short duration of the observation window and Maxim's tendency to invest at an earlier stage than SanDisk, there are also differences in investment objective, funding size, and co-investment that contribute to the exit difference in agreement with the analytical results discussed earlier.

VI.2 Time Warner Investments and AOL Ventures

CVC Group	Parent Corporation	Corporate Sector	Date of First Investment	New Investments in Observation Window[12]	Number of Exits	Fraction Exited
Time Warner Investments	Time Warner Inc.	Media	5/11/1998	22	13	59%
AOL Ventures	AOL Inc.	Internet	12/11/2009	26	10	38%

Table 10: Summary Information for Time Warner Investments and AOL Ventures

Time Warner Investments is the strategic investment arm of Time Warner Inc., a global media and entertainment company that creates, packages, and delivers content through television and other distribution channels. Time Warner Investments targets early to mid-stage companies that "directly enhance Time Warner's ability to meet specific strategic goals … [including] the delivery of new services, enhancement of an existing product, entry or expansion into a key strategic market, completion of a strategic partnership, and critical research and development." At the same time, the group does identify an "attractive financial return potential" as an additional investment criterion (Time Warner Inc., 2014).

AOL Ventures was the venture capital arm of AOL, at the time a leading global provider of internet access and online content, products, and services. AOL Ventures focused on early stage investments (typically Seed and Series A) in consumer internet companies though it categorically did not make strategic investments, instead targeting "outsized financial returns and promotion of

[12] December 2009 – December 2014

AOL's brand within the early stage community.” The group identified a “clear path to exit” as something it looked for in the businesses it invested in (AOL Inc., 2010).

Comparing Time Warner’s primary objective of meeting strategic goals with AOL’s focus on financial returns, it is surprising that the former’s investments during the five-year window achieved a higher rate of exit. One major reason for the discrepancy is Time Warner’s longer CVC experience. Time Warner made its first investment in May 1998, and by the time of the observation window for this comparative case study, had already invested in 67 companies. AOL however, was starting fresh in the space. It is likely that Time Warner’s extensive experience allowed it to identify startup characteristics that met its primary strategic objective but were also predictive of its secondary financial objective, as suggested by the multivariate survival analysis in Section IV.2.

As with Maxim and SanDisk, we see different stage preferences while investing here as well – AOL’s investments tended to be in earlier stage companies than Time Warner (Figure 5). 60% of seed funded startups don’t make it to Series A, and almost half of those that do make it fail to reach Series B. Startups that have raised Series E funding are also almost twice as likely to get acquired as those still in their seed stage (Rowley, 2017). The high failure rate of early stage companies and better odds of exit at later stages helps explain the higher success rates of Time Warner’s mid stage investments relative to AOL’s early stage ones.

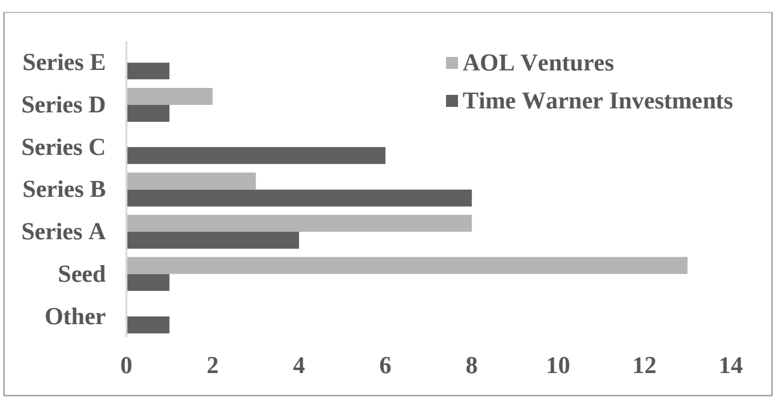

Figure 5: Number of Initial Investments by Stage

As a consequence of investing at later stages and also because of its much bigger size, Time Warner participates in larger funding rounds than AOL, although its funding to market capitalization ratio is smaller (Table 11). The univariate survival analysis shows that both absolute and relative funding size correlate with higher exit probabilities, but the multivariate analysis shows a positive correlation for relative size and a negative correlation for the absolute size. In this case, the positive impact of Time Warner's larger absolute funding sizes appears to be winning out.

CVC Group	**Size of Funding Round**		**Market Capitalization at Investment**		**Funding Size Relative to Market Capitalization**	
	Average	**Median**	**Average**	**Median**	**Average**	**Median**
Time Warner Investments	\$11.7M	\$9.6M	\$44.4B	\$38.1B	0.03%	0.02%
AOL Ventures	\$4.7M	\$3.3M	\$2.5B	\$2.6B	0.24%	0.10%

Table 11: Deal Sizes for Time Warner Investments and AOL Ventures[13]

Finally, co-investment trends between the two CVCs are similar, with AOL having slightly more co-investors on average. Time Warner's investees over the five-year observation window had a higher rate of exit than AOL's had, largely because of the former's greater experience and preference for investing in later stages. This is despite other factors favoring AOL, such as its focus on financial returns, higher relative funding size, and marginally higher presence of co-investors in its deals. Organizational effects likely played a role as well, with CVC being an established activity at Time Warner and a new business at AOL. AOL Ventures also did not have the most stable leadership over the period, with one managing partner frequently being put in operational and integration roles at AOL and its non-venture acquisitions in addition to his Ventures role, and both founding partners leaving by the end of 2013 (Carlson, 2013). Overall, the comparison suggests that experience and long-term organizational support and stability are vital factors for CVC and investee success.

[13] Including both new and follow-on investments

VII. Conclusion

This paper aims to add to the CVC literature along two dimensions. First, it tries to identify if CVC investing elicits a reaction in the corporate parent's stock price. Given the well-recognized long term strategic benefits that corporates gain from CVC activity, as well as market efficiency assumptions that all expected future changes in value as a result of currently known information should be captured in the current stock price, it is reasonable to expect that the stock market will respond positively to such investments. However, the event study results show minimal statistically significant abnormal returns around the investment or exit dates unless investments are segmented by strategic alignment. When this is done, the corporate's stock price shows significant positive abnormal return when there is a sector or industry match between the startup investee and the corporate and a significant negative abnormal return when there is no match. This may be because investors more closely monitor the corporate's actions as it relates to its core business and see strategic investments as sources of innovation or ways to pre-empt competition and reward such activity. In contrast, non-strategic investments are viewed unfavorably, raising questions about the value added by CVC groups that seek purely financial returns.

The second line of investigation in this paper explores how characteristics of the CVC's investment impact the startup's exit probability. While the analysis predictably finds investor experience, relative size of the investment, co-investment, and plentiful funding availability as beneficial to a successful exit, the key finding is that strategic alignment with the corporate lowers exit probability. This decrease can either be explained by misappropriation of the startup's technology by the corporate, or more charitably by selection for objectives not favoring exit. This finding disagrees with Gompers' and Lerner's work and needs to be explored further, perhaps by more rigorously identifying strategic alignment through an examination of business and functional gaps that a startup's product could fill, rather than using a high-level sector or industry assignment as done in this study.

Comparative case studies on selected CVC groups identify another important factor impacting exit, namely the stage that the CVC typically invests in. Since startups at later stages are more likely to survive to the next stage and eventually achieve exit, CVCs that invest at such stages have better exit track records. Along these lines, one of the speakers at the NYU CVC panel mentioned in Section V advised newly established CVC groups to favor later stage investments to get some quick exits and establish credibility with the parent corporation. At the same time, it is possible that access to a corporation's customers and partnerships can enable a startup to scale faster and achieve better stage-to-stage survival rates than a non-CVC backed business, which presents another potential line of inquiry.

Overall, the findings in this paper provide encouragement for a corporate considering sponsorship of a CVC program, as long as it is strategically aligned. They also emphasize the importance of a clear understanding of the corporate's needs, and design of the CVC's mandate and investment process to be aligned with those needs. From the startup's perspective, the paper identifies both positive and negative characteristics to look out for when considering an investment by a CVC, especially concerning IP protections.

VIII. Appendices

VIII.1 Appendix 1 – List of 50 CVC Groups Sampled for Analysis

CVC Group	Corporation	Investment Dates	Number of Investees	Average Number of Co-Investors	Exit Dates	Number of Exits
Intel Capital	Intel Corporation	Dec '95 - Oct '17	1,013	3.8	Sep '98 - Oct '17	427
Qualcomm Ventures	Qualcomm Incorporated	Feb '98 - Oct '17	278	3.3	Jun '99 - May '17	69
Time Warner Investments	Time Warner Inc.	May '98 - Jun '17	113	5.3	Dec '99 - Oct '17	66
Lucent Venture Partners	Lucent Technologies	Aug '96 - Jan '06	53	5.2	Jun '99 - Jan '16	31
Amgen Ventures	Amgen Inc.	Nov '04 - Aug '17	43	4.9	Apr '06 - Feb '17	14
UPS Strategic Enterprise Fund	United Parcel Service, Inc.	Dec '99 - Feb '17	31	5.1	Mar '00 - May '17	12
Citi Ventures	Citigroup Inc.	Aug '07 - Aug '17	39	4.1	Oct '12 - Jan '17	8
American Express Ventures	American Express Company	Aug '12 - Jun '17	35	4.4	Mar '15 - Mar '15	1
AOL Ventures	AOL	Dec '09 - Sep '14	26	5.5	Feb '12 - Aug '17	10
TI Ventures	Texas Instruments Incorporated	Feb '98 - Sep '09	20	6.3	Jun '00 - Sep '15	12
AbbVie Biotech Ventures	AbbVie Inc.	Jun '13 - Oct '17	14	6.9	Dec '16 - Sep '17	1
Amazon Alexa Fund	Amazon.com, Inc.	Jun '15 - Aug '17	25	2.4	Dec '15 - Aug '17	4
Best Buy Capital	Best Buy Co., Inc.	Jul '99 - Feb '17	20	3.4	Feb '02 - Mar '15	9
Agilent Ventures	Agilent Technologies, Inc.	Mar '00 - Feb '06	12	6.6	May '01 - Dec '11	9
CME Ventures	CME Group Inc.	Jun '14 - Jul '17	14	6.1	Aug '16 - Aug '16	1
Constellation Technology Ventures	Exelon Corporation	Jun '09 - Jan '17	12	4.2	Nov '14 - Nov '14	1
Ford Venture Capital Group	Ford Motor Company	Dec '99 - Oct '06	12	5.1	Mar '02 - Mar '15	9
AMD Ventures	Advanced Micro Devices, Inc.	Oct '10 - Jun '15	8	3.3	Oct '11 - Sep '14	3
Maxim Ventures	Maxim Integrated Products, Inc.	Feb '13 - Aug '17	11	1.1		0
SanDisk Ventures	SanDisk	Dec '12 - Mar '16	11	3.4	Oct '13 - Aug '17	5
Zebra Ventures	Zebra Technologies Corporation	Feb '10 - Nov '16	10	1.8	Apr '16 - Apr '16	1
301 INC	General Mills, Inc.	Oct '15 - Sep '17	8	1.4		0
MRL Ventures	Merck & Co., Inc.	Oct '14 - Oct '17	6	6.9	Feb '17 - Feb '17	1

CVC Group	Corporation	Investment Dates	Number of Investees	Average Number of Co-Investors	Exit Dates	Number of Exits
Caterpillar Ventures	Caterpillar Inc.	Aug '15 - May '17	9	2.8		0
EMC Ventures	EMC Corporation	Apr '14 - Aug '15	8	1.6	Jul '15 - Jun '16	2
IBM Watson Group	International Business Machines Corporation	Feb '14 - Dec '16	7	4.6		0
Micron Ventures	Micron Technology, Inc.	May '06 - Nov '10	7	4.0	Aug '09 - Jul '14	5
RGA Ventures	Reinsurance Group of America, Incorporated	Jul '14 - Sep '17	8	6.0		0
Illumina Ventures	Illumina, Inc.	Nov '11 - Sep '17	7	3.7		0
Sinclair Ventures	Sinclair Broadcast Group, Inc.	Jul '98 - Sep '11	6	2.1	Dec '01 - Sep '11	3
Workday Ventures	Workday, Inc.	Jul '15 - Sep '17	7	1.3	Dec '15 - Jun '16	2
Alcatel-Lucent Ventures	Alcatel-Lucent	Nov '09 - Feb '15	4	2.0	Apr '11 - Apr '11	1
ConocoPhillips Technology Ventures	ConocoPhillips	Dec '12 - Jul '16	5	4.7		0
US WEST Internet Ventures	Qwest Communications	Jun '98 - Jan '99	3	6.6	Dec '99 - May '02	3
Lockheed Martin Ventures	Lockheed Martin Corporation	Oct '16 - Sep '17	5	1.6		0
Altria Ventures	Altria Group, Inc.	Jan '12 - Nov '14	4	0.8	May '17 - May '17	1
Boulder Brands Investment Group	Boulder Brands	Jul '13 - Feb '15	3	1.5		0
Chesapeake NG Ventures	Chesapeake Energy Corporation	Jul '11 - Jun '13	2	1.3		0
First Data Ventures	First Data Corporation	Aug '14 - Jan '16	3	1.7	Sep '14 - Sep '14	1
SAP.iO Fund	SAP SE	Mar '17 - Sep '17	3	3.0		0
3D Systems Ventures	3D Systems Corporation	Jun '13 - Apr '17	2	1.5		0
Aetna Ventures	Aetna Inc.	Apr '17 - Aug '17	2	6.0		0
Cerner Health Ventures	Cerner Corporation	May '14 - Feb '17	1	3.5		0
MDC Ventures	MDC Partners Inc.	Jun '15 - Jun '17	2	5.0	May '17 - May '17	1
Optum Ventures	UnitedHealth Group Incorporated	Dec '16 - Mar '17	2	2.5		0
Aflac Corporate Ventures	Aflac Incorporated	Apr '17 - Apr '17	1	1.0		0
Boeing Ventures	The Boeing Company	Aug '03 - Aug '03	1	2.0		0
Constellation Ventures	Constellation Brands, Inc.	Aug '15 - Aug '15	1	0.0		0

CVC Group	Corporation	Investment Dates	Number of Investees	Average Number of Co-Investors	Exit Dates	Number of Exits
DuPont Ventures	E. I. du Pont de Nemours and Company	Sep '14 - Sep '14	1	5.0		0
NJR Clean Energy Ventures	New Jersey Resources Corporation	Sep '12 - Sep '12	1	0.0	Aug '15 - Aug '15	1

VIII.2 Appendix 2 – List of Top-25 Independent Venture Capital Firms

IVC	Number of Deals
New Enterprise Associates	1,864
Kleiner Perkins Caufield & Byers	1,363
Accel Partners	1,209
Sequoia Capital	1,100
Bessemer Venture Partners	1,052
500 Startups	948
Draper Fisher Jurvetson	913
Venrock	809
Lightspeed Venture Partners	781
Norwest Venture Partners	748
Battery Ventures	737
US Venture Partners	679
Khosla Ventures	668
Canaan Partners	668
Greylock Partners	661
Polaris Partners	658
Menlo Ventures	657
Benchmark	652
First Round Capital	648
General Catalyst	626
Andreessen Horowitz	621
Mayfield Fund	612
Index Ventures	612
InterWest Partners	697
CRV	585

VIII.3 Appendix 3 – Capital Overhang Calculation

The capital overhang measure used in this paper draws on two data sources – the first is Thomson ONE Banker's series of non-invested equity from US VC funds raised each month, and the second is the National Venture Capital Association's (NVCA) series of dry powder in US venture capital. The NVCA series cannot be directly used in the analysis since it only has annual values from 2004 to 2016, while the hazard models used in this paper sample time-varying covariates at a monthly level from 1995 to 2017. The Thomson ONE series cannot be used directly either, since it reports undrawn capital from funds raised in each month, and not the absolute level of overhang which would more correctly be a cumulative measure of monthly undrawn capital.

US Venture Capital AUM by Year

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Dry powder ($B)	79.51	82.31	87.91	95.26	93.42	87.32	76.45	76.33	69.61	65.72	72.00	72.21	94.56
Remaining value ($B)	87.44	99.91	125.79	149.98	150.60	174.03	175.02	195.94	197.53	202.18	216.53	242.99	238.93
Total AUM ($B)	166.95	182.22	213.70	245.24	244.02	261.35	251.46	272.27	267.15	267.90	288.53	315.20	333.49

Figure 6: NVCA's US VC dry powder data series (National Venture Capital Association, 2017)

The approach used is to treat the NVCA series as a benchmark and to determine the appropriate length of time over which to take a cumulative sum of the Thomson ONE series to minimize the error from the NVCA series. More specifically, the steps are as follows:

- Calculate rolling sums of the Thomson ONE series for different time periods from one to sixty months
- For each of the sixty series generated, calculate the root mean squared error (RMSE) between the average annual values and the annual values from the NVCA series
- Determine the rolling time period for which the corresponding annual series has the lowest RMSE

The lowest RMSE turns out to be for the 31-month window, so capital overhang is defined as the cumulative sum of the Thomson ONE available equity series for the current month as well as the preceding 30 months.

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