Online Appendix for The Life Cycle of Corporate Venture Capital*

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Appendix A provides additional empirical analyses. Appendix B provides details on the merging process between VentureXpert and USPTO Patent Database. Appendix C discusses the construction of the *Obsolescence* variable and provides additional validation tests. Appendix D provides additional comparisons between CVC and IVCs.

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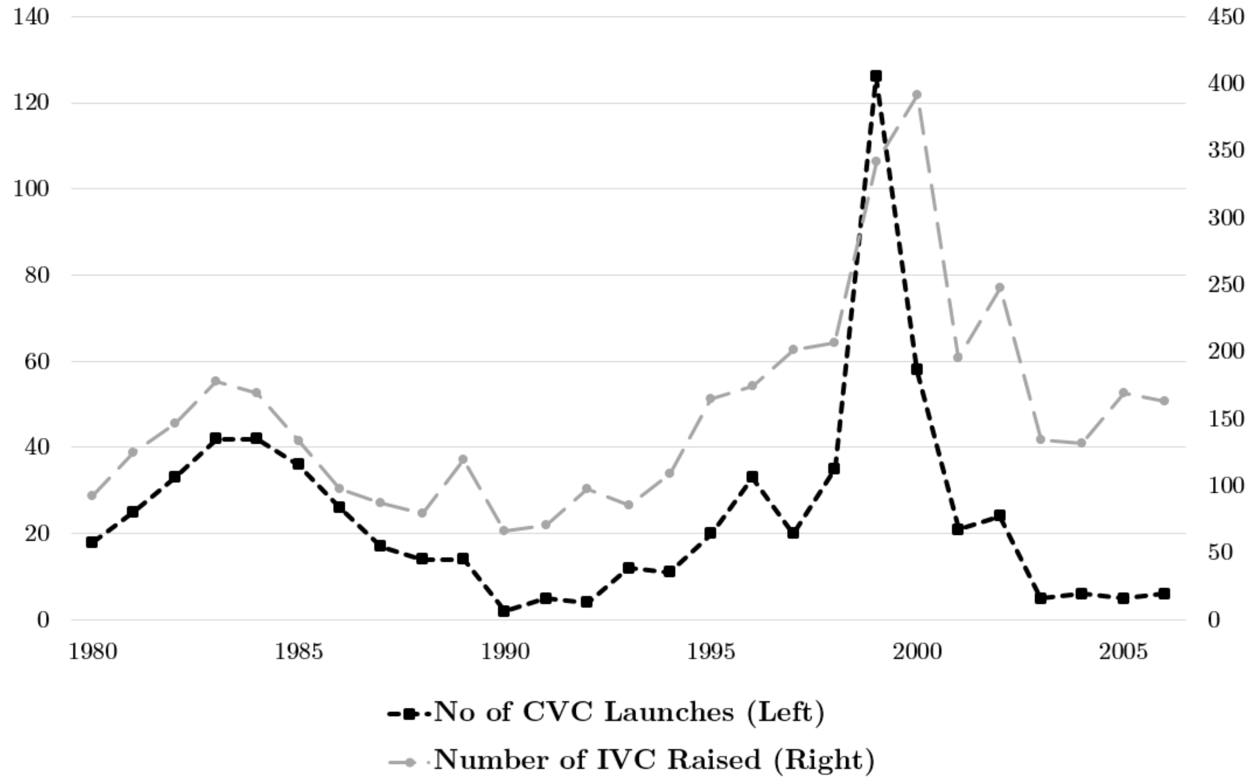
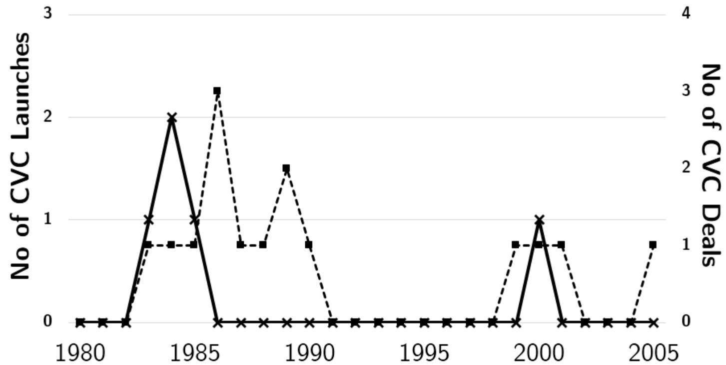
A. Supplementary Results

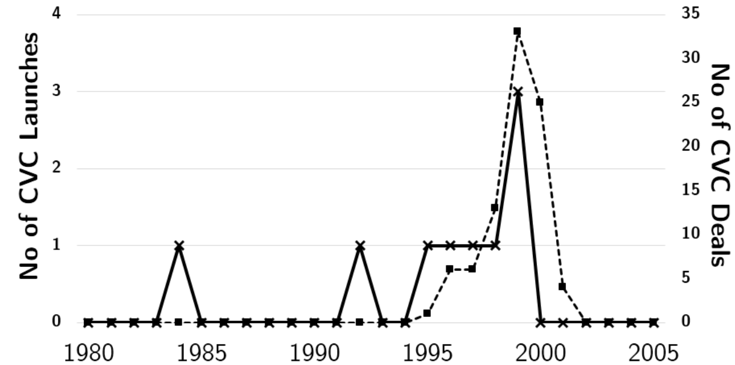
Figure A1. Number of CVC Launches and IVC Launches



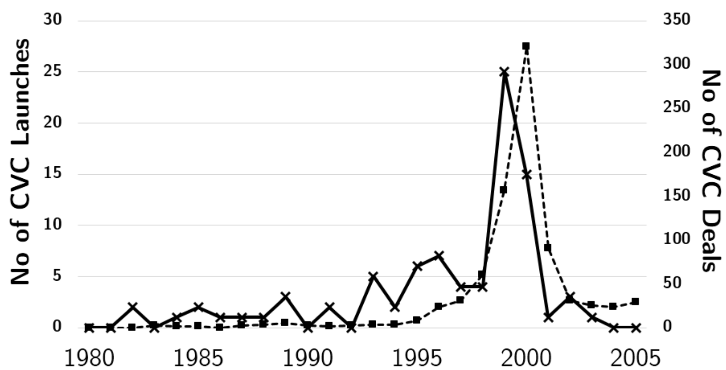
This figure plots the time series of CVC investments covered in the sample. These are CVCs affiliated to US public non-financial firms that were started between 1980 and 2006. The CVC data are from the VentureXpert Venture Capital Firm Database, accessed through Thomson Reuters SDC Platinum. CVC investment is measured as the number of launches of new CVC units (black, left axis). The number of launches of new VC funds is also plotted (gray, right axis).



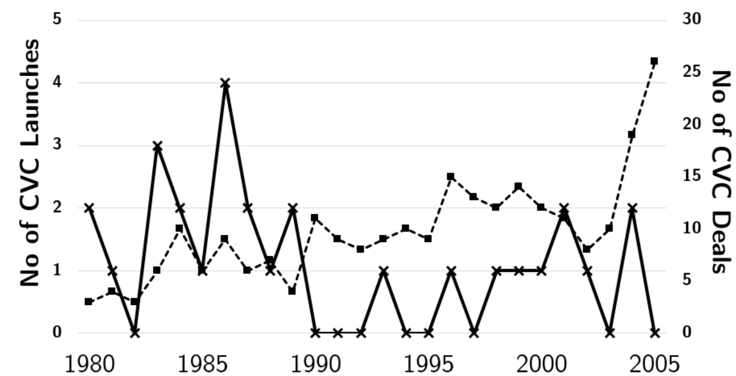
(a) Machinery Industry



(b) Printing and Publishing Industry



(c) IT Industry



(d) Pharmaceutical Industry

Number of CVC Launches   Number of CVC Deals

Figure A2. Time Series of CVC Investment—By Industry

This figure plots the by-industry time series of CVC investments covered in the sample. These are CVCs affiliated to US public non-financial firms that were started between 1980 and 2006. The CVC data are from the VentureXpert Venture Capital Firm Database, accessed through Thomson Reuters SDC Platinum. CVC investment is measured as the launch of new CVC units (left axis) and the number of deals invested in (right axis). CVC deals include only the first investment that a CVC invested in a portfolio company. Industries are classified by the Fama-French 48 Industry Classfications, based on the main SIC code of a firm reported in Compustat.

Table A1
CVC Entries and Investment Deals by Year and Industry

This table provides descriptive statistics on Corporate Venture Capital activities by year (Panel A) and by industry (Panel B). CVCs are identified from the VentureXpert Venture Capital Firm Database, accessed through Thomson Reuters SDC Platinum, and hand-matched to their unique corporate parent firms. CVC parent firms in the sample are US-based public non-financial firms. Panel A reports the annual number of CVC launches (entries) and investment deals between 1980 and 2006. Panel B reports the industry distribution of CVC activities, where industries are defined by the Fama-French 48 Industry Classification.

Panel A: CVC Activities by Year

Year	No. of Launches	No. of Deals	Year	No. of Launches	No. of Deals	Year	No. of Launches	No. of Deals
1980	6	2	1989	9	32	1998	18	155
1981	6	14	1990	2	18	1999	72	460
1982	17	18	1991	4	11	2000	40	891
1983	25	37	1992	2	14	2001	9	430
1984	24	54	1993	9	14	2002	10	211
1985	26	46	1994	5	11	2003	2	179
1986	20	63	1995	16	33	2004	3	229
1987	12	51	1996	18	74	2005	3	255
1988	7	46	1997	15	112	2006	1	194

Panel B: CVC Activities by Industry (Fama-French 48 Industry Classification)

Industry	No. of CVCs	No. of Deals	Industry	No. of CVCs	No. of Deals
Agriculture	2	21	Shipbuilding, Railroad Equipment	1	5
Food Products	2	4	Defense	1	11
Tobacco Products	1	6	Metal Mining	1	6
Entertainment	2	114	Coal	1	4
Printing and Publishing	9	88	Petroleum and Natural Gas	8	10
Consumer Goods	4	48	Utilities	9	48
Healthcare	4	28	Communication	40	120
Medical Equipment	7	109	Business Services	90	821
Pharmaceutical Products	28	254	Computers	44	617
Chemicals	11	48	Electronic Equipment	46	921
Rubber and Plastic Products	2	7	Measuring and Control Equipment	4	32
Textiles	1	2	Business Supplies	2	10
Construction Materials	4	7	Shipping Containers	1	2
Steel Works Etc.	3	15	Transportation	3	9
Machinery	5	15	Wholesale	10	87
Electrical Equipment	9	44	Retail	14	79
Automobiles and Trucks	6	42	Restaurants, Hotels, Motels	4	13
Aircraft	2	7			

Table A2
Innovation Deterioration and CVC Initiation: $\Delta Innovation$ Horizon

This table presents the relation between innovation deterioration and the initiation of Corporate Venture Capital. The analysis is performed using the following specification:

$$I(CVC)_{i,t} = \alpha_{industry \times t} + \beta \times \Delta Innovation_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t},$$

The panel sample is the same as Table 2 in the paper. $I(CVC)_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t and zero otherwise. $\Delta Innovation_{i,t-1}$ is the innovation change over the past four years (that is, the innovation change from $t-5$ to $t-1$) in columns (1) and (2), and over the past two years (that is, the innovation change from $t-3$ to $t-1$) in columns (3) and (4). Innovation is measured using innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one), shown in columns (1) and (3) and innovation quality (the natural logarithm of average citations per new patent in each firm-year plus one), shown in columns (2) and (4). Firm-level controls $X_{i,t-1}$ include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). Industry-by-year dummies are included in the model to absorb industry-specific time trends in CVC activities and innovation. T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	4-Year $\Delta Innovation$		2-Year $\Delta Innovation$	
$\Delta\ln(NewPatent)$	-0.006***		-0.005*	
	(-3.058)		(-1.727)	
$\Delta\ln(Pat.Quality)$		-0.003*		-0.004***
		(-1.827)		(-4.532)
Observations	25,976	25,976	25,976	25,976
Pseudo R-squared	0.114	0.111	0.110	0.107
Industry × Year FE	Yes	Yes	Yes	Yes

Table A3
Determinants of the Entry of Active CVCs

This table examines the determinants of Corporate Venture Capital entry decisions. The analysis is performed using the following specification:

$$I(CVC)_{i,t} = \alpha_{industry \times t} + \beta \times \Delta Innovation_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t},$$

The panel sample is the same as Table 2 with the additional requirement that a CVC to invest in at least two (columns (1) and (2)) or five (columns (3) and (4)) portfolio companies in its life cycle. $I(CVC)_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t and zero otherwise. $\Delta Innovation_{i,t-1}$ is the innovation change over the past three years (i.e., the innovation change from $t-4$ to $t-1$). Innovation is measured using innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one) and innovation quality (the natural logarithm of average lifetime citations per new patent in each firm-year plus one). Firm-level controls $X_{i,t-1}$ include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). The model is estimated using Ordinary Least Squares (OLS). Industry-by-year dummies are included in the model to absorb industry-specific time trends in CVC activities and innovation, and industries are defined by the Fama-French 48 Industry Classification. T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	$I(CVC)=1$			
$\Delta\ln(NewPatent)$	-0.009***		-0.012***	
	(-7.134)		(-8.928)	
$\Delta\ln(Pat.Quality)$		-0.006***		-0.008***
		(-4.644)		(-5.377)
CVC Sample	Investment≥2		Investment≥5	
Observations	25,976	25,976	25,976	25,976
Pseudo R-squared	0.125	0.127	0.146	0.147
Industry × Year FE	Yes	Yes	Yes	Yes

Table A4
Determinants of CVC Entry—Double Clustering

This table examines the determinants of Corporate Venture Capital entry decisions. The analysis is performed using the following specification:

$$I(CVC)_{i,t} = \alpha_{industry \times t} + \beta \times \Delta Innovation_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t}.$$

The analysis follows Table 2 but double-clusters standard errors by both firm and year. $I(CVC)_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t and zero otherwise. $\Delta Innovation_{i,t-1}$ is the innovation change over the past three years (i.e., the innovation change from $t-4$ to $t-1$). Innovation is measured using innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one) and innovation quality (the natural logarithm of average lifetime citations per new patent in each firm-year plus one). Firm-level controls $X_{i,t-1}$ include ROA, size (logarithm of total assets), leverage, R&D ratio (R&D expenditures scaled by total assets), institutional shareholdings and the G-Index. The model is estimated using Ordinary Least Squares (OLS). Industry-by-year dummies are included in the model to absorb industry-specific time trends in CVC activities and innovation, and industries are defined by the Fama-French 48 Industry Classification. T-statistics are shown in parentheses, and standard errors are clustered by firm and by year. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				$I(CVC) = 1$			
$\Delta \ln(NewPatent)$	-0.007***		-0.006***				-0.010**
	(-3.120)		(-2.778)				(1.997)
$\Delta \ln(Pat.Quality)$		-0.004***	-0.004***				-0.004*
		(-3.106)	(-2.647)				(-1.661)
Institutional Shareholding				0.001		-0.002	-0.004
				(0.648)		(-0.134)	(-0.267)
G-Index					0.001	0.001	0.001
					(0.951)	(0.704)	(0.644)
Firm ROA	-0.003	-0.003	-0.003	0.000	-0.012	-0.016	-0.021
	(-1.158)	(-1.359)	(-1.222)	(0.043)	(-0.576)	(-0.690)	(-0.900)
Size (Log of Assets)	0.003***	0.003***	0.003***	0.004***	0.007**	0.008**	0.007*
	(4.495)	(4.509)	(4.390)	(4.759)	(2.346)	(2.266)	(2.079)
Leverage	-0.005*	-0.004*	-0.005*	-0.004	-0.033	-0.034	-0.036
	(-2.010)	(-1.822)	(-2.000)	(-1.537)	(-1.609)	(-1.612)	(-1.613)
Firm R&D	0.015***	0.011**	0.014***	0.017***	0.076**	0.081**	0.081**
	(2.921)	(2.399)	(2.790)	(3.416)	(2.520)	(2.486)	(2.330)
Observations	25,976	25,976	25,976	25,976	5,061	5,061	5,061
R-squared	0.122	0.121	0.122	0.063	0.227	0.208	0.232
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A5
Determinants of CVC Entry—Hazard Model

This table examines the determinants of Corporate Venture Capital entry decisions. The analysis is performed using the following specification:

$$I(CVC)_{i,t} = \alpha_{industry \times t} + \beta \times \Delta Innovation_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t},$$

The panel sample is described in Table 2. $I(CVC)_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t and zero otherwise. $\Delta Innovation_{i,t-1}$ is the innovation change over the past three years (i.e., the innovation change from $t-4$ to $t-1$). Innovation is measured using innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one) and innovation quality (the natural logarithm of average lifetime citations per new patent in each firm-year plus one). Firm-level controls $X_{i,t-1}$ include ROA, size (logarithm of total assets), leverage, R&D ratio (R&D expenditures scaled by total assets), institutional shareholdings and the G-Index. The model is estimated using a hazard model. Industry-by-year stratification is used to absorb industry-specific time trends in CVC activities and innovation, and industries are defined by the Fama-French 48 Industry Classification. T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	$I(CVC) = 1$			
$\Delta \ln(NewPatent)$	-0.896***			
	(-4.702)			
$\Delta \ln(Pat.Quality)$		-0.354***		
		(-3.268)		
Institutional Shareholding			0.158	
			(0.744)	
G-Index				-0.075
				(-0.139)
$exp(\beta)$	0.408	0.702	Not Significant	
Controls	Yes	Yes	Yes	Yes
Observations	25,976	25,976	25,976	5,061
Industry $\times$ Year Stratified	Yes	Yes	Yes	Yes

Table A6
Innovation Deteriorations and CVC Initiations—Different Sampling Criteria

This table documents the relation between innovation deterioration and the initiation of Corporate Venture Capital under different sampling criteria. The analysis is performed using the following specification:

$$I(CVC)_{i,t} = \alpha_{industry \times t} + \beta \times \Delta Innovation_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t},$$

The original panel sample is described in Table 2 in the paper. $I(CVC)_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t and zero otherwise. $\Delta Innovation_{i,t-1}$ is the innovation change over the past three years (i.e., the innovation change from $t-4$ to $t-1$). Innovation is measured using innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one), shown in columns (1) and (3), and innovation quality (the natural logarithm of average citations per new patent in each firm-year plus one), shown in columns (2) and (4). The model is estimated using Two-stage Least Squares, and $\Delta Innovation$ is instrumented using *Knowledge Obsolescence* during the same period as in $\Delta Innovation$. In columns (1) and (2), firms headquartered in California are dropped. In columns (3) and (4), firms in the Business Services industry (categorized using Fama-French 48 industry categorization) are dropped. Firm-level controls $X_{i,t-1}$ include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). Industry-by-year dummies are included in the model to absorb industry-specific time trends in CVC activities and innovation. T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Drop Californian Firms		Drop IT Firms	
$\Delta \ln(NewPatent)$	-0.006***		-0.005***	
	(-4.348)		(-4.150)	
$\Delta \ln(Pat.Quality)$		-0.002***		-0.002**
		(-2.954)		(-2.392)
Observations	21,338	21,338	16,616	16,616
Pseudo R-squared	0.130	0.130	0.120	0.089
Industry × Year FE	Yes	Yes	Yes	Yes

Table A7
Market Misvaluation and the Formation of Active CVCs

This table examines the determinants of Corporate Venture Capital entry decisions. The analysis is performed using the following specification:

$$I(CVC)_{i,t} = \alpha_{industry\times t} + \beta \times \Delta Innovation_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t}.$$

The analysis follows Table 2 in the paper and adds one extra explanatory variable, Firm-specific Overvaluation. This variable is calculated following Rhodes-Kropf, Robinson, and Viswanathan (2005). $I(CVC)_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t and zero otherwise. $\Delta Innovation_{i,t-1}$ is the innovation change over the past three years (i.e., the innovation change from $t-4$ to $t-1$). Innovation is measured using innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one) and innovation quality (the natural logarithm of average lifetime citations per new patent in each firm-year plus one). Firm-level controls $X_{i,t-1}$ include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). The model is estimated using Ordinary Least Squares (OLS). Industry-by-year dummies are included in the model to absorb industry-specific time trends in CVC activities and innovation, and industries are defined by the Fama-French 48 Industry Classification. T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	$I(CVC) = 1$			
Firm-specific Overvaluation	-0.001	-0.001	-0.005	-0.006
	(-0.512)	(-0.587)	(-0.241)	(-0.218)
$\Delta \ln(NewPatent)$	-0.007***		-0.018***	
	(-6.103)		(-10.815)	
$\Delta \ln(Pat.Quality)$		-0.004***		-0.016***
		(-4.268)		(-8.419)
CVC Sample	Full Sample		Only 1999-2000	
Observations	25,976	25,976	4,537	4,537
Pseudo R-squared	0.125	0.121	0.538	0.538
Industry $\times$ Year FE	Yes	Yes	Yes	Yes

Table A8
Determinants of the Formation of CVCs—Remove the IT Bubble (1999-2000)

This table examines the determinants of Corporate Venture Capital entry decisions. The analysis is performed using the following specification:

$$I(CVC)_{i,t} = \alpha_{industry \times t} + \beta \times \Delta Innovation_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t},$$

The analysis uses the sample sample as Table 2 but removes observations in 1999 and 2000. $I(CVC)_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t and zero otherwise. $\Delta Innovation_{i,t-1}$ is the innovation change over the past three years (i.e., the innovation change from $t-4$ to $t-1$). Innovation is measured using innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one) and innovation quality (the natural logarithm of average lifetime citations per new patent in each firm-year plus one). Firm-level controls $X_{i,t-1}$ include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). The model is estimated using Ordinary Least Squares (OLS). Industry-by-year dummies are included in the model to absorb industry-specific time trends in CVC activities and innovation, and industries are defined by the Fama-French 48 Industry Classification. T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	$I(CVC) = 1$	
$\Delta \ln(NewPatent)$	-0.006***	
	(-5.967)	
$\Delta \ln(Pat.Quality)$		-0.004***
		(-3.812)
Observations	21,439	21,439
Pseudo R-squared	0.125	0.127
Industry × Year FE	Yes	Yes

Table A9
Innovation Deterioration and CVC Initiation—The Role of Uncertainty

This table documents the relation between innovation deterioration and CVC initiations across firms with heterogeneous informational environments. The analysis is performed using the specification based on Table 2. Observations are categorized into two subgroups by the median of uncertainty level of the firm's informational environment, which is measured using the average dispersion of patent quality in a technology class weighted by the technological distribution of the firm's portfolio over technology classes. The measure is formally calculated as follows: in the first step, for each technology class c categorized by the USPTO, I calculate its patent quality dispersion in year t as the standard deviation of lifetime citations of all patents applied under class c in year t, and I further standardize this standard deviation by the mean of these patents' lifetime citations to make it comparable across technology classes. A higher quality dispersion captures the content that there are various innovation routes at the time that eventually lead to very different outcomes. In the second step, I calculate each firm i's exposure to different classes in year t, ω_{ict} as the number of i's patents in c divided by the number of its total patents, as of year t. In the last step, I calculate the firm-year level uncertainty measure by weighting the class-year uncertainties in step one using the firm-year weights in step two. Columns (1) and (2) focus on the subsample of firms with higher innovation uncertainty, and columns (3) and (4) focus on the subsample of firms with lower innovation uncertainty. T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$I(CVC)$		$I(CVC)$	
	(1)	(2)	(3)	(4)
$\Delta \ln(NewPatent)$	-0.010***		-0.003**	
	(-3.268)		(-2.535)	
$\Delta \ln(Pat.Quality)$		-0.005***		-0.002*
		(-2.833)		(-1.883)
Subsample	High Innovation Uncertainty		Low Innovation Uncertainty	
Observations	13,878	13,878	12,098	12,098
R^2	0.118	0.113	0.106	0.101
Industry × Year FE	Yes	Yes	Yes	Yes

Table A10
The Financial View at the CVC Entry Stage

This table presents evidence to further assess the financial view of CVC entry. Panel A examines whether CVC entries are accompanied by declines of internal R&D. The empirical model correlates innovation input and the entry of CVCs, where innovation input is measured using R&D expenditures scaled by total assets (columns (1) and (3)) or scaled by sales (columns (2) and (4)).

In Panel B, I examine whether innovation deteriorations motivate financial or strategic CVCs using the same specification as in Table 3, except that the dependent variable distinguishes financial and strategic CVCs. I categorize CVCs in the sample into financial- or strategic-driven by collecting information disclosed at the announcement of CVC initiations using a news search, following a similar approach as Dushnitsky and Lenox (2006). For each CVC in the sample, I search for media coverage and corporate news at its initiation using LexisNexis, Factiva, and Google. Based on this compiled information, CVCs are coded as financial and strategic. In columns (1) and (2), the dependent variable is a dummy that takes value one if the firm launches a CVC in that year and indicates that the CVC is for strategic purposes; in columns (3) and (4) the dependent variable is a dummy that takes value one if the firm launches a CVC in that year and indicates that the CVC is mainly financial return-driven.

In all regressions, firm-level controls $X_{i,t-1}$ include the ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). Industry-by-year dummies are included in the model to absorb industry-specific time trends in CVC activities and innovation. T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation Input and CVC Entries

	$I(CVC)$		$I(CVC)$	
	(1)	(2)	(3)	(4)
$\Delta R\&D/Assets$	0.005*		0.001	
	(1.957)		(0.234)	
$\Delta R\&D/Sales$		0.001		-0.004
		(0.229)		(-0.730)
$\Delta \ln(NewPatent)$			-0.008***	-0.009***
			(-5.394)	(-5.155)
$\Delta \ln(Pat.Quality)$			-0.002***	-0.003***
			(-3.096)	(-3.649)
Observations	25,976	25,976	25,976	25,976
Pseudo R-squared	0.064	0.092	0.132	0.135
Industry × Year FE	Yes	Yes	Yes	Yes

Panel B: Strategic vs. Financial CVCs

	I(Strategic CVC)		I(Financial CVC)	
	(1)	(2)	(3)	(4)
$\Delta \ln(NewPatent)$	-0.013***		-0.002	
	(-3.722)		(-1.414)	
$\Delta \ln(Pat.Quality)$		-0.007**		-0.001
		(-2.318)		(-1.528)
Observations	25,976	25,976	25,976	25,976
R^2	0.199	0.193	0.083	0.077
Industry × Year FE	Yes	Yes	Yes	Yes

Table A11
Corporate Venture Capital's Selection of Portfolio Companies—Diversification

This table studies how CVCs select portfolio companies. I construct a cross-sectional data set by pairing each CVC i with each entrepreneurial company j that had ever received investment from a VC. I remove cases in which the active investment years of CVC firm i (between initiation and termination) and active financing years of company j (between the first and the last round of VC financing) do not overlap. The analysis is performed using the following specification:

$$\begin{aligned} I(CVC_i\text{-}Target_j) = \alpha + \beta_D \times I(Diversifying) \\ + \beta_0 \times I(DeterioratingAreas) + \beta_1 \times TechProximity_{ij} + \beta_2 \times KnowledgeOverlap_{ij} \\ + \beta_3 \times Local_{ij} + \beta_4 \times Distance_{ij} + \gamma \times X_{i,j} + \varepsilon_{i,j}, \end{aligned}$$

where the dependent variable, $I(CVC_i\text{-}Target_j)$, is equal to one if CVC i actually invests in company j (realized pairs) and zero otherwise. The analysis follows Table 6 and adds an additional independent variable $I(Diversifying)$. $I(Diversifying)$ takes value one if the startup's innovation areas are all outside the CVC parent's innovation areas, and zero otherwise. The Appendix defines explanatory variables more formally. CVC (i)-level characteristics include the number of annual patent applications and the average number of citations of patents; I also control for those innovation characteristics at the startup (j)-level. T-statistics are shown in parentheses, and standard errors are clustered by CVC firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$I(CVC_i\text{-}Target_j)$				
	(1)	(2)	(3)	(4)	(5)
$I(Diversifying)$	-0.025***	-0.025***	-0.024***	-0.025***	-0.024***
	(-4.515)	(-4.392)	(-4.257)	(-4.222)	(-4.182)
$I(DeterioratingAreas)$	0.011**	0.011**	0.011*	0.011*	0.011*
	(2.031)	(2.002)	(1.923)	(1.857)	(1.755)
Technological Proximity		0.031**	0.034**	0.035**	0.035**
		(2.264)	(2.135)	(2.073)	(2.291)
Knowledge Overlap			-0.020**	-0.019**	-0.019**
			(-2.001)	(-2.107)	(-1.998)
Local				-0.010***	-0.011***
				(-2.935)	(-2.767)
$\ln(Distance)$					-0.010***
					(-4.924)
Observations	868,323	868,323	868,323	847,102	847,102
R^2	0.127	0.127	0.127	0.130	0.130
CVC-level Controls	Yes	Yes	Yes	Yes	Yes
Startup-level Controls	Yes	Yes	Yes	Yes	Yes

Table A12
Corporate Venture Capital's Selection of Portfolio Companies—One by One

This table studies how CVCs select portfolio companies. I construct a cross-sectional data set by pairing each CVC i with each entrepreneurial company j that had ever received investment from a VC. I remove cases in which the active investment years of CVC firm i (between initiation and termination) and active financing years of company j (between the first and the last round of VC financing) do not overlap. The analysis is performed using the following specification:

$$I(CVC_i\text{-}Target_j) = \alpha + \beta_0 \times I(DeterioratingAreas) + \beta_1 \times TechProximity_{ij} + \beta_2 \times KnowledgeOverlap_{ij} \\ + \beta_3 \times Local_{ij} + \beta_4 \times Distance_{ij} + \gamma \times X_{i,j} + \varepsilon_{i,j},$$

where the dependent variable, $I(CVC_i\text{-}Target_j)$, is equal to one if CVC i actually invests in company j (realized pairs) and zero otherwise. The analysis follows Table 6 but the explanatory variables enters the regression one by one. The Appendix defines explanatory variables more formally. CVC (i)-level characteristics include the number of annual patent applications and the average number of citations of patents; I also control for those innovation characteristics at the startup (j)-level. T-statistics are shown in parentheses, and standard errors are double-clustered by CVC firm and startups. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$I(CVC_i\text{-}Target_j)$				
	(1)	(2)	(3)	(4)	(5)
$I(DeterioratingAreas)$	0.012**				
	(2.074)				
Technological Proximity		0.034**			
		(2.482)			
Knowledge Overlap			0.014*		
			(1.937)		
Local				-0.010***	
				(-2.775)	
$\ln(Distance)$					-0.007**
					(-2.253)
Observations	868,323	868,323	868,323	847,102	847,102
R^2	0.137	0.137	0.137	0.137	0.137
CVC-level Controls	Yes	Yes	Yes	Yes	Yes
Startup-level Controls	Yes	Yes	Yes	Yes	Yes

Table A13
Corporate Venture Capital's Selection of Portfolio Companies—Active CVCs

This table studies how CVCs select portfolio companies. I construct a cross-sectional data set by pairing each CVC i with each entrepreneurial company j that had ever received investment from a VC. I remove cases in which the active investment years of CVC firm i (between initiation and termination) and active financing years of company j (between the first and the last round of VC financing) do not overlap. The analysis is performed using the following specification:

$$I(CVC_i\text{-}Target_j) = \alpha + \beta_0 \times I(DeterioratingAreas) + \beta_1 \times TechProximity_{ij} + \beta_2 \times KnowledgeOverlap_{ij} + \beta_3 \times Local_{ij} + \beta_4 \times Distance_{ij} + \gamma \times X_{i,j} + \varepsilon_{i,j},$$

where the dependent variable, $I(CVC_i\text{-}Target_j)$, is equal to one if CVC i actually invests in company j (realized pairs) and zero otherwise. The analysis follows Table 6 with the additional requirement that the CVC invest in at least two or five startups in its life cycle. The Appendix defines explanatory variables more formally. CVC (i)-level characteristics include the number of annual patent applications and the average number of citations of patents; I also control for those innovation characteristics at the startup (j)-level. T-statistics are shown in parentheses, and standard errors are clustered by CVC firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$I(CVC_i\text{-}Target_j)$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$I(DeterioratingAreas)$	0.012**	0.012**	0.012**	0.012**	0.011**	0.014**	0.014**	0.014**	0.014**	0.014**
	(2.211)	(2.176)	(2.157)	(2.183)	(2.095)	(2.535)	(2.428)	(2.409)	(2.386)	(2.372)
Technological Proximity		0.029**	0.031**	0.031**	0.031**		0.032**	0.037**	0.037**	0.037**
		(2.196)	(2.137)	(2.035)	(2.012)		(2.351)	(2.310)	(2.279)	(2.153)
Knowledge Overlap			-0.018**	-0.016**	-0.016**			-0.019**	-0.018**	-0.018**
			(-2.034)	(-2.091)	(-2.007)			(-2.237)	(-2.206)	(-2.186)
Local				-0.010***	-0.011***				-0.010***	-0.012***
				(-2.879)	(-2.793)				(-2.749)	(-2.727)
$\ln(Distance)$					-0.010***					-0.012***
					(-4.653)					(-3.855)
CVC Sample			Investment≥2					Investment≥5		
Observations	805,937	805,937	805,937	799,328	799,328	677,296	677,296	677,296	649,871	649,871
R^2	0.137	0.137	0.137	0.141	0.141	0.151	0.151	0.151	0.174	0.174
CVC-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A14
Corporate Venture Capital's Selection of Portfolio Companies—Double Clustering

This table studies how CVCs select portfolio companies. I construct a cross-sectional data set by pairing each CVC i with each entrepreneurial company j that had ever received investment from a VC. I remove cases in which the active investment years of CVC firm i (between initiation and termination) and active financing years of company j (between the first and the last round of VC financing) do not overlap. The analysis is performed using the following specification:

$$I(CVC_i\text{-}Target_j) = \alpha + \beta_0 \times I(DeterioratingAreas) + \beta_1 \times TechProximity_{ij} + \beta_2 \times KnowledgeOverlap_{ij} + \beta_3 \times Local_{ij} + \beta_4 \times Distance_{ij} + \gamma \times X_{i,j} + \varepsilon_{i,j},$$

where the dependent variable, $I(CVC_i\text{-}Target_j)$, is equal to one if CVC i actually invests in company j (realized pairs) and zero otherwise. The analysis follows Table 6 and cluster standard errors both at the investing CVC and the startup level. The Appendix defines explanatory variables more formally. CVC (i)-level characteristics include the number of annual patent applications and the average number of citations of patents; I also control for those innovation characteristics at the startup (j)-level. T-statistics are shown in parentheses, and standard errors are double-clustered by CVC firm and startups. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$I(CVC_i\text{-}Target_j)$				
	(1)	(2)	(3)	(4)	(5)
$I(DeterioratingAreas)$	0.012**	0.012*	0.012*	0.012**	0.011*
	(2.074)	(1.915)	(1.903)	(2.008)	(1.856)
Technological Proximity		0.029**	0.031**	0.031*	0.031*
		(2.112)	(1.993)	(1.951)	(1.892)
Knowledge Overlap			-0.018*	-0.016*	-0.016*
			(-1.874)	(-1.826)	(-1.798)
Local				-0.010***	-0.011***
				(-2.775)	(-2.692)
ln($Distance$)					-0.010***
					(-4.658)
Observations	868,323	868,323	868,323	847,102	847,102
R^2	0.137	0.137	0.137	0.141	0.141
CVC-level Controls	Yes	Yes	Yes	Yes	Yes
Startup-level Controls	Yes	Yes	Yes	Yes	Yes

Table A15
Corporate Venture Capital's Selection of Portfolio Companies—Non Booming Period

This table studies how CVCs select portfolio companies. I construct a cross-sectional data set by pairing each CVC i with each entrepreneurial company j that had ever received investment from a VC. I remove cases in which the active investment years of CVC firm i (between initiation and termination) and active financing years of company j (between the first and the last round of VC financing) do not overlap. The analysis is performed using the following specification:

$$I(CVC_i\text{-}Target_j) = \alpha + \beta_0 \times I(DeterioratingAreas) + \beta_1 \times TechProximity_{ij} + \beta_2 \times KnowledgeOverlap_{ij} + \beta_3 \times Local_{ij} + \beta_4 \times Distance_{ij} + \gamma \times X_{i,j} + \varepsilon_{i,j},$$

where the dependent variable, $I(CVC_i\text{-}Target_j)$, is equal to one if CVC i actually invests in company j (realized pairs) and zero otherwise. The analysis follows Table 6 but CVCs that were initiated in 1999 and 2000 are dropped from the regression. CVC (i)-level characteristics include the number of annual patent applications and the average number of citations of patents; I also control for those innovation characteristics at the startup (j)-level. T-statistics are shown in parentheses, and standard errors are clustered by CVC firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$I(CVC_i\text{-}Target_j)$				
	(1)	(2)	(3)	(4)	(5)
$I(DeterioratingAreas)$	0.014**	0.014**	0.014**	0.014**	0.012**
	(2.358)	(2.221)	(2.046)	(2.019)	(1.983)
Technological Proximity		0.031**	0.034**	0.034**	0.035***
		(2.497)	(2.553)	(2.541)	(2.689)
Knowledge Overlap			-0.022**	-0.017**	-0.018**
			(-2.362)	(-2.346)	(-2.529)
Local				-0.013***	-0.012**
				(-3.727)	(-2.215)
ln($Distance$)					-0.011***
					(-6.253)
Observations	654,986	654,986	654,986	642,652	642,652
R^2	0.132	0.132	0.132	0.134	0.134
CVC-level Controls	Yes	Yes	Yes	Yes	Yes
Startup-level Controls	Yes	Yes	Yes	Yes	Yes

Table A16
Integrating Innovation Complementarities from CVC Investments—Early vs. Late Stages

This table studies whether CVC parents incorporate their portfolio companies' technological knowledge in their own internal R&D by following Table 7 in the paper. Column (1) and (3) reports the same average results as Table 7. Columns (2) and (4) separately estimate the intensity of citing knowledge possessed by companies in which the CVC invest at early vs. late stages. The categorization of early vs. late is based on the median of startup age at the time of the first investment by a CVC. Columns (3) and (6) separately estimate the intensity of citing knowledge possessed by companies that either exit successfully (acquired or publicly listed) or eventually fail. All specifications include CVC (i)-level characteristics including number of annual patent applications, average citations of patents, and controls for those innovation characteristics at the startup (j)-level. T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Citing a Startup's Patents		Citing a Startup's Knowledge	
$I(CVC\text{-}Portfolio) \times I(Post)$	0.197***		0.361***	
	(4.538)		(8.196)	
$\times EarlyStage$		0.205***		0.378***
		(6.712)		(8.224)
$\times LateStage$		0.190**		0.345***
		(2.183)		(3.948)
$I(CVC\text{-}Portfolio)$	0.013		0.028	
	(1.104)		(1.344)	
$I(Post)$	0.025		0.039	
	(1.235)		(1.187)	
Firm-level Controls	Yes		Yes	
Startup-level Controls	Yes		Yes	
Observations	71,305		71,305	
R-squared	0.264		0.231	

Table A17
Integrating Complementarities through Inventor Adjustment

This table studies the role of human capital renewal in CVC parent firms' information acquisition process. The Harvard Business School Patent Database provides inventor-level information that allows me to identify inventor mobility, characteristics of the inventor team for each patent, and the specific technologies used by each inventor in her/his innovation.

Panel A: Inventor Mobility during CVC Operation

Panel A studies inventor mobility accompanying CVC investment. The analysis is based on the following standard difference-in-differences (DiD) framework:

$$y_{i,t} = \alpha_{FE} + \beta \cdot I(CVCParent)_i \times I(Post)_{i,t} + \beta' \cdot I(CVCParent)_i + \beta'' \cdot I(Post)_{i,t} + \gamma \times X_{i,t} + \varepsilon_{i,t}.$$

The sample consists of CVCs and their propensity score-matched control firms. The dependent variables $y_{i,t}$ are the logarithm of inventor leavers (columns (1) and (2)), the logarithm of newly hired inventors (columns (3) and (4)), and the proportion of patents mainly contributed by new inventors (columns (5) and (6)). A patent is considered as mainly contributed by new inventors if at least half of the inventor team has three or fewer years' experience in the firm in the patenting year. $I(CVCParent)_i$ is a dummy variable indicating whether firm i is a CVC parent firm or a matched control firm. $I(Post)_{i,t}$ indicates whether the firm-year observation is within the $[t+1, t+5]$ window after (pseudo-) CVC initiations. All specifications include industry-by-year fixed effects $\alpha_{industry \times t}$ to absorb time-variant industrial technological trends, or firm and year fixed effects. Firm-level control variables include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(1+Leavers)$		$\ln(1+NewHires)$		Ratio of New Inventors' Pat	
$I(CVCParent) \times I(Post)$	0.119***	0.078*	0.110***	0.086**	0.171**	0.154*
	(3.478)	(1.896)	(2.791)	(2.142)	(2.402)	(1.948)
$I(CVCParent)$	0.015		0.019		-0.073	
	(1.217)		(1.380)		(-0.240)	
$I(Post)$	0.023	0.052*	0.003	0.037**	0.069	-0.024
	(1.297)	(1.921)	(0.149)	(2.360)	(0.774)	(-0.385)
Observations	6,859	6,859	6,859	6,859	3,223	3,223
R-squared	0.220	0.633	0.235	0.659	0.275	0.440
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	No	Yes	No	Yes	No
Year FE	No	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No	Yes

Panel B: New Inventors and New Information

Panel B studies the intensity of using newly acquired knowledge by new inventors in internal innovation. In column (1), the sample consists all the patents produced by CVC parents and matched control firms from five years before the event to five years after the event. The unit of observation is one patent. $I(CVCParent)$ is a dummy variable indicating whether the patent is filed by a CVC parent firm or a matched control firm. $I(Post)$ indicates whether the patent is filed within the $[t+1, t+5]$ window after (pseudo-) CVC initiations. $I_{\text{New Inventor's Pat}}$ equals one if new inventors contribute at least half of the patent. The dependent variable, *New Cite Ratio*, is calculated as the ratio of citations made by patents that the producing firm never cited before. Column (2) studies who implements more knowledge directly acquired from invested startups in CVC parents. The analysis therefore focuses on the cross-sectional sample of patents produced by CVC parent firms during the five-year window after CVC initiation, and the dependent variable is an indicator of whether the patent cites the CVC's portfolio companies' patents. Column (1) includes industry-by-year fixed effects $\alpha_{industry \times t}$ to absorb time-variant industrial technological trends. Firm-level control variables include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) *New Cite Ratio*	(2) *Citing Portfolio*
$I_{\text{New Inventors' Pat}} \times I(CVCParent) \times I(Post)$	0.031**	
	(2.364)	
$I_{\text{New Inventors' Pat}} \times I(CVCParent)$	0.007	
	(0.368)	
$I_{\text{New Inventors' Pat}} \times I(Post)$	-0.009	
	(-0.753)	
$I_{\text{New Inventors' Pat}}$	0.050***	0.121***
	(4.621)	(4.354)
$I(CVCParent) \times I(Post)$	0.069***	
	(2.656)	
$I(CVCParent)$	-0.041	
	(-1.570)	
$I(Post)$	-0.015	
	(-0.888)	
Observations	132,407	41,397
R-squared	0.151	0.126
Controls	Yes	Yes
Industry × Year FE	Yes	–

Table A18

Determinants of the Termination of More Active CVCs' Life Cycle

This table studies the decision to terminate Corporate Venture Capital. The regressions are performed on the panel of CVCs in their active years. The analysis follows Table 10 with the additional requirement that the CVC must invest in at least two or five startups in its life cycle. The dependent variable is a CVC termination dummy, and the specification is estimated using a hazard model. In columns (1), (2), (6) and (7) the key variable $\Delta Innovation_{i,t}$ is defined as the difference of innovation between year t and the year of initiation. In columns (3) to (5) and (8) to (10) the key variables of interest are governance-related proxies including institutional shareholding, G-Index, and an event dummy of CEO turnover. Firm-level control variables include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CVC Termination									
$\Delta \ln(NewPatent)$	0.368***					0.389***				
	(5.921)					(5.623)				
$\Delta \ln(Pat.Quality)$		0.297***					0.301***			
		(6.486)					(6.018)			
Institutional Shareholding			0.052					0.097		
			(0.153)					(0.298)		
G-Index				0.056					0.038	
				(0.457)					(0.537)	
CEO Turnover					0.025					0.019
					(0.509)					(0.582)
CVC Sample	Investment≥2					Investment≥5				
$exp(\beta)$	1.445	1.346	Not Significant			1.476	1.351	Not Significant		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,217	2,217	2,217	2,217	2,217	1,983	1,983	1,983	1,983	1,983

Table A19
Determinants of the Termination of CVC Life Cycle—Evidence Around Termination and Hibernation Coding

This table studies the decision to terminate Corporate Venture Capital. The regressions are performed on the panel of CVCs in their active years. The dependent variable is a CVC termination dummy, and the specification is estimated using a hazard model. In columns (1) and (2) the key variable $\Delta Innovation_{i,t}$ is defined as the difference of innovation between year t and the year of initiation. In columns (3) to (5) the key variables of interest are governance-related proxies including institutional shareholding, G-Index, and an event dummy of CEO turnover. The table follows Table 10 but considers CVCs that hibernate in the CVC period as exit and re-enter later, where hibernation is defined as entering a consecutive no-investment period of at least half of the total CVC life cycle. Firm-level control variables include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	CVC Termination				
$\Delta\ln(NewPatent)$	0.312***				
	(4.912)				
$\Delta\ln(Pat.Quality)$		0.232***			
		(5.935)			
Institutional Shareholding			0.053		
			(0.097)		
G-Index				0.022	
				(0.443)	
CEO Turnover					0.009
					(0.183)
$exp(\beta)$	1.366	1.261	Not Significant		
Controls	Yes	Yes	Yes	Yes	Yes
Observations	2,233	2,233	2,233	2,233	2,233

B. Merging VentureXpert with Patent Databases

In this section, I describe the process to merge entrepreneurial companies in the VentrueXpert database with USPTO patent databases through matching company names in VentureXpert with assignee names in the USPTO patent database. To minimize potential problems introduced by the minor discrepancy between different versions of the USPTO database, I use both NBER and the Harvard Business School (HBS) patent databases to provide patent assignee information. After this step, each company in VentureXpert has its original name, standardized name, and a stem name; similar for USPTO assignees.

B.1. Name Standardization

I begin by standardizing company names in VentureXpert and assignee names from NBER and the HBS patent databases using the name standardization algorithm developed by the NBER Patent Data Project. This algorithm standardizes common company prefixes and suffixes and strips names of punctuation and capitalization; it also isolates a company's stem name (the main body of the company name), excluding these prefixes and suffixes.

B.2. The Matching Procedure

With these standardized and stem company (assignee) names and demographic information provided by both VentureXpert and the USPTO, I merge the databases following the matching procedures below:

1. Each standardized VentureXpert company name is matched with standardized names from the NBER data and HBS data.

(a) If an exact match is identified, I consider this as a "$\boxed{\textit{successful match}}$." The company is removed from the set of names waiting to be matched on both sides.

(b) Otherwise, next step.

2. Each stem VentreXpert company name is matched with stem names from the NBER data and HBS data.

   (a) If an exact match of stem names is identified and the two companies are located in the same city and state OR if the two companies are located in the same state and the earliest patenting year in NBER and HBS databases is later than the founding year in VentureXpert, I consider this as a "$\boxed{\textit{successful match}}$." The company is removed from the set of names waiting to be matched on both sides.

   (b) If an exact match of stem names is identified, but the two companies do not satisfy the location and chronology criteria above, I consider this as a "$\boxed{\textit{potential match}}$." The company is moved to a pool of firms waiting for manual checks.

   (c) Otherwise, next step.

3. For the remaining companies, each stem VentureXpert company name is matched with up to three close stem names from the USPTO data using a fuzzy-matching method based on the Levenshtein edit distance.[1] The criterion is based on the length of the strings and the Levenshtein distance, and the threshold is determined through a random sampling procedure.

   (a) If the fuzzy-matched pair is located in the same city and state OR if the two companies are located in the same state and the earliest patenting year in NBER and HBS databases

[1]The Levenshtein edit distance measures the degree of proximity between two strings and corresponds to the number of substitutions, deletions, or insertions needed to transform one string into the other one (and vice versa).

is later than the founding year in VentureXpert, I consider this as a "$\boxed{\textit{potential match}}$."

(b) Otherwise, the companies are categorized as "$\boxed{\textit{failed to match}}$."

4. The "$\boxed{\textit{potential matches}}$" set identified in the procedures above is reviewed by hand, incorporating information from both data sources, including full patent abstracts and company business descriptions.

   (a) Pairs confirmed as successful matches through the manual check are moved to the "$\boxed{\textit{successful match}}$" set.

C. *Obsolescence*: Descriptions and Validity

This appendix provides more discussions on the variable *Knowledge Obsolescence* (or *Obsolescence* for short), which is used in the paper as a source of variation to firms' capability of innovating independent of contemporaneous managerial behaviors. This discussion includes the theoretical background, details in construction and validity tests, as well as acknowledging potential limitations and how those limitations are mitigated in the paper.

C.1. The Conceptual Idea and Its Roots

The proposition that knowledge obsolescence affects innovation has its roots in four basic observations. First, knowledge begets knowledge. Isaac Newton said, "If I have seen further it is by standing on the shoulders of Giants." Indeed, the knowledge stock of an innovative individual or institution determines the quantity and quality of its innovation and knowledge production. This observation has been formalized and discussed in several strands of literature (see Jones (2009) and the papers cited therein).

Second, knowledge ages. Since the 1950s, several disciplines have developed the concept of the obsolescence of knowledge/skills/technology. The most famous result might be, roughly speaking, that half of our knowledge today will be of little value (or even proven wrong) after a certain amount of time (i.e., its half-life), and this half-life is becoming shorter and shorter (Machlup, 1962). In economics, people have studied the effect of obsolescence of knowledge and skills on labor, industrial organization, and aggregate growth (Rosen, 1975).

Third, predicting knowledge trends is difficult, if not impossible. Even though mathematicians and bibliometricians have been developing mathematical models to fit the half-life dynamics of the overall knowledge stock, predicting the trend for each specific stock has not been successful. Indeed, it is this "impossibility" that creates the possibility of creative destruction and the fading of generations of firms.

Fourth, knowledge absorption can be difficult and slow. For any individual or institution, knowledge can be identified, absorbed, and managed at a limited rate. Even for firms, which have the option to replace human capital (innovators), the adjustment costs and uncertainty associated with the matching process limits their ability to do so.

Based on these observations, *Knowledge Obsolescence* proxies for a shock to the value and usefulness of knowledge possessed by each firm, which in turn affects innovation performance of the firm. Following Newton's metaphor, when a firm is already on the shoulder of a standing Giant, the *Obsolescence* measure captures a shock to the height of the Giant (to make the Giant sit or jump, for example), and this shock exogenously determines how far the firm can see.

C.2. Variable Construction

Obsolescence attempts to capture an exogenous technological variation that is independent of a firm's recent operations but that influences the firm's innovation performance. For each firm i in year t, this instrument is constructed in three steps. First, I define firm i's predetermined knowledge space in year $t-\tau$ as all the patents cited by firm i (but not belonging to i) up to year $t-\tau$. Then, I calculate the number of citations received by this $KnowledgeSpace_{i,t-\tau}$ in $t-\tau$ and in t, respectively. Last, $Obsolescence^{\tau}_{i,t}$ is defined as the change between the two, and a more negative *Obsolescence* means a larger decline of the value of a firm's knowledge:

$$Obsolescence^{\tau}_{i,t} = -[\ln(Cit_t(KnowledgeSpace_{i,t-\tau})) - \ln(Cit_{t-\tau}(KnowledgeSpace_{i,t-\tau}))].$$

Simply put, this instrument first defines the knowledge space of a firm by incorporating detailed information on the firm's innovation profile and citation history ("tree") and then measures the rate of obsolescence using exogenous citation dynamics to this knowledge space.

C.3. Validity Tests

For the instrument to be empirically valid, it must strongly affect the future innovation productivity of a firm. This instrument affects firms' innovation performance through multiple channels. A negative shock to the value of a firm's knowledge space implies a longer distance to the knowledge frontier and a higher knowledge burden to identify valuable ideas and to produce radical innovation (Jones, 2009). Firms working in a fading area will benefit less from knowledge spillover (Bloom, Schankerman, and Van Reenen, 2013), which in turn will dampen the innovation and productivity growth.

The impact of the obsolescence instrument on innovation is empirically illustrated in the first-stage regression as presented in Table 3 of the paper and reproduced below in Table A20 column (1). The estimate of -0.114 in column (1) translates a 10% increase in the rate of obsolescence of a firm's knowledge space into a 1.14% decrease in its patent applications; this same change is associated with a 1.28% decrease of its patent quality as shown in column (2). The F-statistics of these first-stage regressions are both well above the conventional threshold for weak instruments (Stock and Yogo, 2005). In columns (3) and (4), I present the first stages using an alternative instrument where the knowledge space of a firm is constructed based on its citations made before $t-10$. The first-stage regressions hold robust with this alternative construction.

Another identifying assumption is monotonicity, which requires that the *Knowledge Obsolescence* variable has a monotonic impact on innovation productivity. This means that while the

Table A20
First-stage regressions

	(1) $\Delta\ln(NewPatent)$	(2) $\Delta\ln(Pat.Quality)$	(3) $\Delta\ln(NewPatent)$	(4) $\Delta\ln(Pat.Quality)$
Obsolescence	-0.114***	-0.128***	-0.052***	-0.053***
	(-12.165)	(-17.064)	(-9.619)	(-9.648)
Measure	*Obsolescence*		10-year *Obsolescence*	
Controls	Yes	Yes	Yes	Yes
F-Statistic	147.99	291.18	92.53	93.08
Observations	25,976	25,976	20,145	20,145
R-squared	0.398	0.370	0.294	0.215
Industry $\times$ Year FE	Yes	Yes	Yes	Yes

instrument may have little effect on some firms, all those which are affected are affected in the same way directionally. In other words, the assumption would be violated if the knowledge obsolescence variable were negatively associated with innovation in certain types of firms, while it were positively associated with innovation in other firms. This implies that the first-stage estimates should be non-positive for all subsamples.

Table A21 below displays first-stage regression coefficients for several subsamples. The full sample is divided based on the total number of patents owned in a firm's patent stock, based on the age of the firm in the specific year (where age is measured using the IPO year as a start) and based on the time periods. As we can see, the estimates are negative and sizable in all subsamples, in line with the monotonicity assumption.

A particularly important test is the one that concerns market competition. Viewing the instrument through the lens of the competition-innovation literature, one interpretation of the instrument is that if the technologies on which the firm is relying are less cited, it might be because the firm is facing less competition, which may increase the firm's incentive to innovate in this area (since it is less likely to be imitated). If this interpretation of the instrument were true, even for only a small subsample of firms, the monotonicity assumption would be violated and the message conveyed in the reduced form regression would be very different. I test the first stage on subsamples with different levels of competition—if the competition-innovation line of thinking were valid, one may expect it to show up in a more competitive industry where patent racing is in place. When examining by-industry HHI subsamples, the first-stage regressions are strong in both subsamples. Moreover, it is important to point out that citations are generally considered to be relevant to patent value (Kogan et al., 2017), so this "fewer citations-better profits" concern is further mitigated.

Table A21
First stage heterogeneities

		$\Delta\ln(NewPatent)$		$\Delta\ln(Pat.Quality)$	
	Obs	First-stage Coef	F-stat	First-stage Coef	F-stat
	(1)	(2)	(3)	(4)	(5)
Full Sample	25,976	-0.114***	147.99	-0.128***	291.18
Size (patent stock)					
High patent stock	14,563	-0.124***	98.55	-0.132***	215.74
Low patent stock	11,413	-0.106***	76.13	-0.125***	187.32
Firm age					
Younger	12,537	-0.095***	54.25	-0.115***	152.11
Older	13,439	-0.132***	105.66	-0.140***	222.64
Time periods					
1980-1989	5,017	-0.089***	32.23	-0.097***	99.41
1990-1999	11,342	-0.121***	74.25	-0.138***	184.52
2000-	9,617	-0.110***	62.17	-0.131***	168.32
Industry competition					
High industry competition	13,598	-0.105***	72.59	-0.121***	198.53
Low industry competition	12,378	-0.123***	84.21	-0.132***	218.37

At this point, it is worth furthering the discussion on the validity of the exclusion restriction for using this instrument in the CVC study. This identification strategy is designed to overcome the fact that corporate innovation performance could be affected by complicated economic forces that can also affect CVC investment decisions. For example, one important threat to the OLS interpretation is that poorly governed firms may experience poor innovation performance and initiate CVC as a managerial perk at the same time. Having the problem in mind, the validity of this approach rests on the assumption that, controlling for industry-specific technological trends (using industry-year fixed effects) and firm-specific characteristics (using an extensive set of controls), the measured obsolescence of a firm's knowledge space predetermined years ago is orthogonal to its current CVC strategy, other than through affecting current innovation performance. Two important threats to the empirical strategy are that

- One might worry that a firm's knowledge space might be affected by the type and capability of managers; yet this concern should be allayed by using a predetermined knowledge space formed along the corporate history rather than the concurrent one.
- One might also worry that the firm itself could be the main driver of the technological evolution. This concern is addressed first by excluding patents owned by the firm from its own knowledge space and by excluding all citations made by the firm itself in the variable construction. It is further mitigated by a robustness check on a subsample of medium and small firms, which are less likely to endogenize technological evolution.

C.4. A Simple Illustrative Example Using the Instrument

To illustrate how the instrumental variable can correct the estimation bias raising from the endogeneity problem, I describe the following simple example.[2] Assume that a firm's probability of launching a CVC unit is determined by an unconditional probability and an incremental probability determined by $\Delta Innovation$ realized in the near past, formulated as $P_{CVC} + q \cdot \Delta Innovation$.

[2] This example is based on ben (2010) and Bernstein (2015).

P_{CVC} stands for the unconditional probability of CVC initiations, and $\Delta Innovation$ is a dummy indicating whether the firm experienced an innovation increase ($\Delta Innovation = 1$) or an innovation deterioration ($\Delta Innovation = -1$). I make $\Delta Innovation$ a binary dummy to simplify the illustration.

Suppose that the unconditional probability of launching a CVC is heterogeneous and is correlated with $\Delta Innovation$ in some endogenous way (e.g., manager type could be driving both at the same time). Specifically, assume that there are three types of firms based on their ability to innovate: *High*-type firms are on an upward trajectory innovation ($\Delta Innovation = 1$ unconditionally) and have an unconditional probability of launching CVC $P_{CVC} = p_H$. *Sensitive*-type firms are sensitive to technological evolution and will have $\Delta Innovation = 1$ (-1) if the technology trend works in favor of (against) them, and these firms have a type-specific CVC probability of $P_{CVC} = p_M$. *Low*-type firms are in a struggling situation ($\Delta Innovation = -1$ unconditionally) and $P_{CVC} = p_L$. For simplicity, assume that the knowledge obsolescence will be either *favorable* or *disruptive* to the firm, each with probability 50%, and each firm type is with probability 1/3. In the table below, we can summarize the probability of initiating a CVC unit in the six possible cases:

	Obsolescence	
Firm Type	Favorable	Disruptive
High	$\Delta Innovation = 1$ $p_H + q$	$\Delta Innovation = 1$ $p_H + q$
Sensitive	$\Delta Innovation = 1$ $p_M + q$	$\Delta Innovation = -1$ $p_M - q$
Low	$\Delta Innovation = -1$ $p_L - q$	$\Delta Innovation = -1$ $p_L - q$

The OLS estimates essentially compare firms that experience an innovation increase ($\Delta Innovation = 1$, the upper left triangle) with the firms that experience an innovation deterioration ($\Delta Innovation =$

-1, the bottom right triangle), and the result reflects both the "treatment effect" and the selection bias (from the heterogeneity of P_{CVC}):

$$\begin{aligned}\beta_{OLS} &= \frac{1}{1-(-1)} \times \{E[Y|\Delta Innovation = 1] - E[Y|\Delta Innovation = -1]\} \\ &= q + \frac{1}{3} \times (p_H - p_L).\end{aligned} \tag{A1}$$

The bias term, $(1/3) \times (p_H - p_L)$, could be either positive or negative based on the assumption on the order of $\{p_H, p_M, p_L\}$. On the one hand, if we assume that bad governance could be driving both innovation decline and CVC initiation, then $p_L > p_H$ and β_{OLS} is more negative than the true effect q. On the other hand, if we assume that forward-looking managers could be driving both innovation improvements and CVC business, then $p_L < p_H$ and β_{OLS} is more positive than q. The true size of the bias is hard to ascertain under this framework.

The IV approach uses the exogenous variation in *Obsolescence*, which affects $\Delta Innovation$, to help back out the true q. The "first-stage" regression captures the effect of *Obsolescence* on $\Delta Innovation$:

$$\frac{1}{1-(-1)} \times \{E[\Delta Innovation|Favorable] - E[\Delta Innovation|Disruptive]\} = \frac{1}{3}. \tag{A2}$$

The reduced-form estimates the effect of *Obsolescence* on CVC activities, in the form of:

$$\frac{1}{1-(-1)} \times \{E[Y|Favorable] - E[Y|Disruptive]\} = \frac{1}{3}q. \tag{A3}$$

The IV estimate is the ratio between the reduced-form and the first-stage estimates, that is,

$$\beta_{IV} = \frac{E[Y|Favorable] - E[Y|Disruptive]}{E[\Delta Innovation|Favorable] - E[\Delta Innovation|Disruptive]} = q. \tag{A4}$$

To conclude this example, I wish to highlight two points. First, as shown in the derivation, the IV approach essentially uses only the "*Sensitive*" group to estimate the true q, or, in technical terms, the estimation relies on the "Local Average Treatment Effect" (LATE) based on the "compliers" (the observations that are responsive to the instrument). Second, both $\Delta Innovation$ and $Obsolescence$ take binary values in this example for simplicity. Obviously, those two variables both take continuous value in the data—the example's derivation can be extended to this case by weighting-average the estimates along the support of the instrument.

D. Comparing Investment Patterns of CVC and IVC

In this appendix, I document stylized facts on CVC investment patterns that complement main empirical explorations in Sections 2 to 4.

D.1. Investment Characteristics

First, I contrast CVCs with traditional independent VCs (IVCs) among various investment dimensions. The relevant variables and their definitions are provided below.

Variable	Definition and Construction
A. Investor-specific Features	
Duration	The duration of a fund, calculated as the period between the initiation and the termination dates.
Active Years of Investment	The number of years in which the investor made investments in new ventures.
Number of Companies Invested	The number of companies in which the investor invested through its life cycle.
B. Investor-startup-pair Level Information	
Innovative Startup	A dummy variable indicating whether the startup in the deal owned at least one patent at the time of investment, identified using the merged VentureXpert and USPTO data.
Age at Initial Investment	The age of the portfolio company at the time that the investor made its first investment.
Round of Initial Investment	The round number in which the investor made its first investment in the specific company.
Round 1, 2, ..., 5 and Above	A set of dummies that equal to one if the first time that the investor participated was the company's first, second, third, fourth, or fifth and above round, and zero otherwise.

# of Syndicating VCs	The total number of venture capital firms that syndicated in the round(s) in which the investor participated.
Geographic Distance	The distance, in kilometers, between the entrepreneurial venture and the investor location.
Local Startup	A dummy variable that takes value one if the investor and the startup are in the same Commuting Zone (CZ).
IPO	A dummy variable that takes the value of one if the venture went public, and zero otherwise, calculated for companies that were at least six years old as of March 2015.
Acquisition	A dummy variable that takes the value of one if the venture was acquired, and zero otherwise, calculated for companies that were at least six years old as of March 2015.

In the table below I present investment patterns of the whole sample (including both CVCs and IVCs). The two types separately, along with tests for the statistical significance of the differences in means across the CVC sample and the IVC sample. In Panel A, the unit of analysis is a VC fund. In Panel B, the unit of analysis is a unique pair of an investor and a startup.

Stylized Fact 1: The CVC Life Cycle. *CVCs on average are temporary corporate divisions, staying through nonuniform life cycles that are shorter than IVCs.*

I start by examining the staying power and investment time horizons of CVCs. As opposed to IVCs, which typically follow a standard contractual horizon of 10 to 12 years (Barrot, 2016), or internal R&D units, which are structured as perpetual components, CVCs appear to be temporary corporate divisions that have short investment horizons. Specifically, the median duration of a CVC is four years, and the mean is around six years, more than 30% shorter than that of an IVC. I also examine the number of years that an investor makes new investments in new startups, i.e., active years, which is 3.92 (3) years at the mean (median), only about half of IVCs' active years.

The short life cycle is not likely to be explained by the potential concern that CVCs make poor investments and therefore fail to survive the venture business. When comparing the ratio of going public or being acquired across startups that are backed by CVCs and IVCs, I find that CVC-backed companies do slightly better in these successful exit dimensions, i.e., 14.09% vs. 12.57% for IPO, 36.89% vs. 34.37% for acquisitions. In earlier studies, both Gompers and Lerner (2000) and Chemmanur, Loutskina, and Tian (2014) show that CVC-backed companies perform at least as well as those backed by IVCs based on future exit outcomes.[3] The result is also unlikely to be affected by the natural attrition rates of parent firms—when restricting the CVC sample to parents that survive for at least three years beyond their CVC terminations, the pattern holds strongly.

Stylized Fact 2: Innovation-oriented. *CVCs disproportionately invest in entrepreneurial ventures that are innovation-intensive.*

What kind of companies do CVCs invest in? One striking observation is that CVCs disproportionately invest in innovation-intensive startups. Compared to a proportion of 18.49% in IVCs' portfolios, more than half of CVCs' portfolio companies have patented at least once at the time of investment. The limitation of using "patenting" to capture "innovativeness" is that it misses startups conducting unpatentable research. However, Farre-Mensa, Hegde, and Ljungqvist (2017) and Hochberg, Serrano, and Ziedonis (2017) show that patents are crucial in determining startup innovation value and subsequent growth and thereby are arguably the most important intellectual properties of the startup. Overall, this fact suggests that CVCs value innovation-related strategic benefits.

Stylized Fact 3: Distinct Investment Patterns. *CVCs invest in earlier stages, syndicate more, and*

[3] Admittedly, using exit outcomes such as IPO or acquisitions cannot fully reflect investment returns, which is a common data limitation. Lerner (2012) provides an in-depth discussion on cases of CVCs not making profitable investments.

show weaker home bias.

CVCs tend to invest in slightly younger companies in earlier rounds. On average, CVCs make their first investment in a startup when the startup is 3.2 years old, while IVCs start to invest when a venture is around 4.1 years old. In terms of financing rounds, CVCs start to invest in the middle of the third and the fourth financing rounds, while IVCs on average make their initial investment closer to the fourth round. After breaking down each round, it appears that CVCs concentrate their investments in the second and third rounds, and they are less likely to invest in very early rounds (round one or seed) or later rounds (round five and above). Geographically, the average distance between CVC investors and their portfolio ventures is longer compared to IVCs and their portfolio companies, and CVCs are less likely to invest at home (startups in the same Commuting Zone). CVCs are also more likely to form syndications with other VCs.

D.2. Industry Focus

Next I examine the industry focus of CVCs and IVCs. These new analyses and discussions document an interesting trend in CVC investment: the CVC-backed portfolio deviates from the traditional VC-backed portfolio, and this deviation is *more* pronounced during active VC waves. This is in line with the paper's main argument about the special strategic goal of CVC investments.

The methodology of comparing VC-CVC portfolio industry focuses stems from two strands of finance literature. Below, I will first discuss the original methodologies and then how they are adapted to the setting of VC-CVC comparison.

- The first method intends to measure the deviation of CVCs' portfolio weights from independent VCs. I borrow the method developed by the literature on active fund management that calculates the portfolio deviation of a fund manager from the index fund (Cremers and

Petajisto, 2009), i.e., "active shares." To adapt the method to the VC-CVC setting, I calculate, for each calendar year, a weighting vector by computing the proportion of CVC investments in each industry, where industry is calculated using the 3-digit industry code from VentureXpert, $\omega_{CVC,t}$ (I acknowledge that industry codes in VentureXpert differ from the SIC system, but fortunately this is irrelevant to the task here). Specifically, each component $\omega_{CVC,t,i}$ in the vector is the weight of investments in the specific industry i calculated as the number of CVC-backed deals in industry i divided by the total number of CVC-backed deals in year t. I also create the same weighting vector for VC investments, $\omega_{IVC,t}$. Both $\omega_{CVC,t}$ and $\omega_{IVC,t}$ are $1 \times N$-vectors, with N being the number of industries and the weights in industry i in year t denoted as $\omega_{\cdot,t,i}$. The $\Delta Portfolio(CVC, IVC)$ is formally defined as

$$\Delta Portfolio_t(CVC, IVC) = \frac{1}{2} \times \Sigma_{i=1}^{N} |\omega_{CVC,t,i} - \omega_{IVC,t,i}|.$$

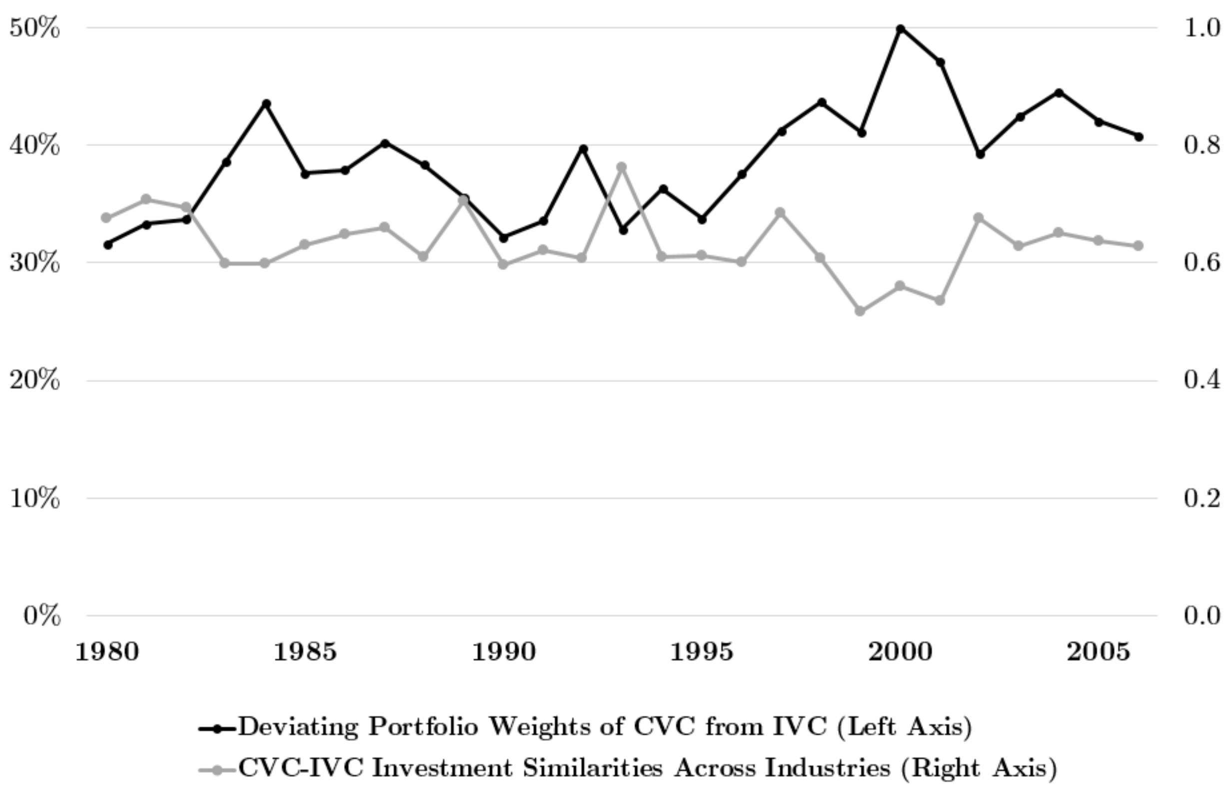
Intuitively, this measure captures how much the aggregate CVC portfolio deviates from the IVC portfolio. In one extreme case, if CVCs completely replicate IVCs' investment allocation, the measure $\Delta Portfolio(CVC, IVC)$ will take value 0%. In another extreme case, if CVCs invest in completely different industries as IVCs with no overlap (say in a world with only two industries, A and B, where CVCs only invest in A, while VCs only invest in B), the measure $\Delta Portfolio(CVC, IVC)$ will take value 100%. $\Delta Portfolio_t(CVC, IVC)$ will be bounded in the range of 0% and 100%.

- The second method intends to measure the similarity between CVC and IVC portfolios by calculating the Cosine similarities of $\omega_{CVC,t}$ and $\omega_{IVC,t}$, formally defined as

$$PortfolioSimilarity_t(CVC,IVC) = \frac{\omega_{CVC,t}\omega'_{IVC,t}}{\sqrt{\omega_{CVC,t}\omega'_{CVC,t}}\sqrt{\omega_{IVC,t}\omega'_{IVC,t}}}.$$

On top of the level of deviations as captured by $\Delta Portfolio_t(CVC,IVC)$, this measure effectively picks up the similarities of CVC and IVC industry focuses. A higher similarity means that CVCs and IVCs keep a similar balance across different industries, and vice versa.

Figure A3. Comparing CVC and IVC Portfolio Focus



In Figure A3, I plot both $\Delta Portfolio_t$ (black, left axis) and $PortfolioSimilarity_t$ (gray, right axis) from 1980 to 2006, where for each year the weighting vectors are created using the investments made in the focal calendar year. Based on this figure, CVC and IVC portfolios' industry focuses are different during the sample period, with the deviation of portfolio weight being roughly 35% and the similarity being roughly 0.6. This is different from a case in which a CVC replicates and IVC's strategies, which would yield a 100% and 1.

Perhaps more interestingly, the deviation widens and similarity decreases during "waving" VC years, in which, presumably, there were more deals done for the purpose of investing in "hot" areas. The fact that CVCs are not following these trends as much provides additional support that CVCs have different intentions when making investment decisions.

Descriptive Investment Patterns of CVC vs. IVC

This table presents investment patterns of CVCs and IVCs. Summary statistics are provided for the whole sample (including both CVCs and IVCs). The two types separately, along with tests for the statistical significance of the differences in means across the CVC sample and the IVC sample. In Panel A, the unit of analysis is a VC fund. In Panel B, the unit of analysis is a unique matching between a venture investor and a startup company. All variables are defined above.

	Whole Sample		CVC		IVC		T-test (CVC vs. IVC)
	Mean	Median	Mean	Median	Mean	Median	*p*-value
Panel A: Fund Level Statistics							
Duration (years)	8.59	9	6.22	4	9.27	10	0.00***
Active years of investment	6.42	6	3.92	3	7.14	6	0.00***
Number of companies invested	16.61	5	13.14	4	17.61	5	0.00***
Panel B: Investment Level Statistics							
Innovative Startup	25.47%	0%	51.93%	100%	18.49%	0%	0.00***
Age at initial investment	3.95	3.6	3.26	3.2	4.13	3.8	0.00***
Round of initial investment	3.81	3	3.59	3	3.87	3	0.03**
Round 1	18.53%	0.00%	14.99%	0.00%	19.46%	0.00%	0.00***
Round 2	19.62%	0.00%	22.66%	0.00%	18.82%	0.00%	0.00***
Round 3	17.18%	0.00%	19.43%	0.00%	16.59%	0.00%	0.00***
Round 4	13.68%	0.00%	15.17%	0.00%	13.29%	0.00%	0.06*
Round 5 and above	30.99%	0.00%	27.75%	0.00%	31.84%	0.00%	0.00***
# of syndicating VCs	5.47	4	6.83	6	5.11	4	0.00***
Geographical Distance	1,429.51	535.23	1,662.49	1,134.34	1,368.03	514.75	0.04**
Local Startup	23.79%	0	21.23%	0	24.47%	0	0.02**
IPO	12.89%	0	14.09%	0	12.57%	0	0.04**
Acquisition	34.90%	0	36.89%	0	34.37%	0	0.07*

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