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RESEARCH ARTICLE

THE ROLE OF VENTURE CAPITAL IN THE FORMATION OF A NEW TECHNOLOGICAL ECOSYSTEM: EVIDENCE FROM THE CLOUD

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Appendix A

Correlation Matrix

	VC	Cloud	C/S Product Experience	Sales	Trademarks	Patents	Age	Location in (CA, TX, MA)
VC	1							
Cloud	0.305	1						
C/S product experience	0.275	0.187	1					
Sales	0.086	0.159	0.075	1				
Trademarks	-0.063	0.070	0.057	0.105	1			
Patents	0.140	0.102	0.018	0.044	0.081	1		
Age	-0.099	0.013	0.117	0.169	-0.088	-0.045	1	
Location in (CA, TX, MA)	0.212	0.016	0.051	0.099	0.070	0.134	-0.129	1

Notes: The correlation matrix is based on the 2009 sample, a total of 231 firms.

Appendix B

Robustness Check, Multinomial Logit Model

Table B1. Complementarity between VC and Cloud

VARIABLES	Cloud Only (1)	VC Only (2)	Both VC and Cloud (3)
Constant	-2.542*** (0.298)	-1.991*** (0.250)	
Sales	0.023** (0.012)	0.027 (0.019)	
Trademarks	1.169 (0.832)	-10.211*** (3.459)	
Patents	0.173 (0.214)	0.351* (0.213)	
C/S product experience	0.013 (0.012)	0.052*** (0.015)	
Age	0.006 (0.037)	-0.081** (0.038)	
Location in (CA,TX,MA)	-0.519 (0.507)	0.291 (0.449)	
Non-IT M&A		1.169** (0.517)	
Complementarity θ			1.733*** (0.473)

Notes: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The regression is based on 2009 sample, a total of 231 firms.

Table B2. Whether the Complementarity Is Stronger When a Firm Is Backed by a VC with Rich IT Experience

	Cloud Only	VC with Little Experience	VC with Rich Experience	Cloud and VC with Little Experience	Cloud and VC with Rich Experience
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Constant	-2.546*** (0.301)	-2.450*** (0.300)	-3.070*** (0.429)		
Sales	0.023** (0.011)	0.027 (0.023)	0.026 (0.020)		
Trademarks	1.178 (0.827)	-10.607** (4.431)	-9.605** (4.067)		
Patents	0.208 (0.192)	0.434** (0.219)	0.220 (0.233)		
C/S product experience	0.017 (0.012)	0.059*** (0.015)	0.037** (0.016)		
Age	0.003 (0.038)	-0.097** (0.046)	-0.060 (0.048)		
Location in (CA,TX,MA)	-0.593 (0.525)	0.250 (0.576)	0.378 (0.563)		
Non-IT M&A		0.805 (0.647)	1.706** (0.758)		
Complementarity θ1				1.155* (0.652)	
Complementarity θ2					2.304*** (0.546)
Difference between θ1 and θ2				1.149* (0.671)	

Notes: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The regression is based on 2009 sample, a total of 231 firms.

Table B3. Whether the Complementarity Is Weaker When a Firm Has Rich Experience in Existing C/S Products

	Cloud Only	VC Only	Both VC and Cloud
VARIABLES	**(1)**	**(2)**	**(3)**
Constant	-2.542*** (0.306)	-1.981*** (0.248)	
Sales	0.022* (0.011)	0.027 (0.020)	
Trademarks	1.159 (0.911)	-10.518*** (3.400)	
Patents	0.136 (0.218)	0.357 (0.223)	
C/S product experience	0.043** (0.018)	0.064*** (0.017)	
Age	0.013 (0.039)	-0.083** (0.038)	
Location in (CA, TX, MA)	-0.351 (0.731)	0.157 (0.446)	
Non-IT M&A High		1.152** (0.519)	
Complementarity (θ)			1.752***
C/S product experience (δ)			-0.040*

Notes: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The regression is based on 2009 sample, a total of 231 firms.

Appendix C

Complementarity Analysis Using Panel Data with Instrumental Variables

In this appendix, we describe in detail how we test for complementarity using instrumental variables in conjunction with our panel-data fixed-effects approach. We do not emphasize this result for several reasons. First, instrumenting for only one decision using this approach may not provide consistent parameter estimates (Arora 1996). Second, given our use of within-firm variation in this model, we must rely on a different set of exclusion restrictions from those in our baseline approach.

Our first step is to identify variables that are likely correlated with a firm's likelihood to receive VC but is uncorrelated with a firm's new product development strategy. As in our baseline multinomial probit model, we seek to identify exclusion restrictions that influence the supply of local VC funding but are unlikely to influence a firm's product development strategy. Because we use within-firm variance for identification in this section, we adapt and augment our exclusion restriction from the baseline analysis.

The sources of our first two instrumental variables are based upon successful exits from local VC-backed investments. The logic is similar to that described for our baseline exclusion restriction: successful exits from prior rounds of VC investments will increase the returns to local limited partners (LPs). Because LPs invest in local VCs and VCs also invest locally, this will increase the likelihood of VC funding to a start-up, all things being equal. First, as in our baseline analysis, we use the number of M&As (mergers & acquisitions) from VC-backed non-IT firms in the start-up's home state in the previous two years. Our second variable is the total dollar value of VC-backed initial public offerings (IPOs) in all non-IT industries in the start-up's home state in the previous two years. We use the value of VC-backed IPOs rather than the number because it is more closely correlated with returns; however, we have experimented with using the number of IPOs as a robustness check, and the results are qualitatively similar.

Our third variable is motivated by prior research in the VC literature that has used the number of local limited partners as a source of variation that will influence the likelihood and extent of VC funding that firms will receive (Chemmanur et al. 2011; Samila and Sorenson 2010, 2011). Specifically, we use the number of limited partners that invested in VC funds during the prior five years (excluding the focal year) and are located in the same state. Again, the number of limited partners is correlated with the likelihood that a firm will receive VC funding but is unlikely to be correlated with its product strategy, as LPs usually do not directly interact with portfolio companies.

We use a dummy measure for these three variables (i.e., it equals 1 if it is above the 50^{th} percentile and 0 otherwise) to incorporate potential nonlinearities of their effects on VC funding. Further, because the number and incidence of VC deals changes during our sample, we interact each of them with a linear time trend (denoted *High M&As × time trend*, *High IPOs × time trend*, and *High limited partners × time trend*).

Following prior literature (Angrist and Pischke 2009), our second step is to employ a probit model to predict the likelihood that a firm will receive VC funding using these three variables as the predictors. The results are reported in column (1) in Table C1. The next step is to use the predicted likelihood of receiving VC funding from this probit model in column (1) as the instrument in the second-stage regression. Using nonlinear fitted values of instruments in this way has been shown to have greater efficiency than a traditional linear first stage for binary endogenous variables but still provides consistent estimates (Angrist 2001; Newey 1990).

The results from the first- and second-stage regression are included in columns (2) and (3) in Table C1 respectively. As expected, in the first stage, the predicted value of the likelihood of receiving VC financing based on the above three factors is strongly correlated with a firm's true VC funding status. The *F*-statistic is 15.94, above the commonly used threshold of 10. The results from the second stage show that the sign of the coefficient of VC is consistent with the baseline fixed-effects model result, although the magnitude and standard error are somewhat higher.

Table C1. Explore the Complementarity between VC Financing and Offering Cloud, Instrumental Variable Estimation

	Probit Model with DV as Whether Firm *i* in Year *t* Had Received VC	Fixed Effects Linear Probability Model with Instrumental Variable			
		First Stage		Second Stage	
	(1)		(2)		(3)
High M&As X time trend	.043*** (.014)	Predicted prob. of receiving VC funding	.404*** (.101)	VC	.311* (.188)
High IPOs X time trend	-.017 (.016)	Sales	-.001 (.001)	Sales	.002** (.001)
High limited partners × time trend	.074*** (.015)	Trademarks	.002 (.028)	Trademarks	-.014 (.022)
		Patents	.003 (.013)	Patents	.001 (.009)
		C/S product experience	.003** (.001)	C/S product experience	.002 (.001)
Year dummies	Yes	Year dummies	Yes	Year dummies	Yes
Firm fixed effect	No	Firm fixed effect	Yes	Firm fixed effect	Yes

Notes: Heteroskedasticity robust standard errors clustered over firms are in parentheses.
*Significant at 10%; **Significant at 5%; ***Significant at 1%.

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