Social Capital, Density, and Startup Survival:

An Empirical Study Using the Kauffman Firm Survey

Cesar Bandera
Assistant Professor of Entrepreneurship
bandera@njit.edu

Ellen Thomas
Associate Professor of Marketing
ellen.thomas@njit.edu

Martin Tuchman School of Management
New Jersey Institute of Technology

Abstract

The high density of firms in incubators and clusters could positively impact their regional economy simply due to their sheer number of startups they launch, but the failure rate of these startups is not significantly greater than that of startups elsewhere. This lackluster performance at the level of the individual firm is all the more striking given the opportunity for social capital diffusion in these high density regions, and the importance of social capital to startup success. We hypothesize that a being in an environment in which social capital is readily accessible does not imply that the startup will engage it. This work presents a life table model and a parametric exponential model of startup survival that distinguishes between the density of the startup ecosystem and its exploitation. Using the longitudinal Kauffman Firm Survey of 4928 companies founded in 2004 and the US Census Bureau County Business Patterns, we compute the density of a startup's ecosystem as the number of companies in the startup's ZIP code with the startup's 2-digit North American Industry Classification System code. We find a strong positive association between startup survival and its collaborations with other agents (universities, industries, and government organizations). These collaborations are not correlated with density, although we find that survival improves slightly with density for high tech startups and worsens slightly for non-tech startups. This work suggests that instead of focusing on the

development of human capital among their tenants, incubator and cluster managers should encourage startups to develop their social capital.

1. Introduction: Conflicting Effectiveness Measures of Business Incubators and Clusters

Similar businesses will tend to cluster geographically (Porter 2000, Stuart and Sorenson 2003, Gilbert, McDougall et al. 2008) in order to benefit from access to relevant resources including specialized staff, venture capital, suppliers, and support services (Saxenian 1996). Business incubators and business clusters are such regions characterized by a high density of companies addressing similar markets and managed by universities, municipalities or states/provinces so as to promote regional economic development (Porter 2000, Van Geenhuizen and Soetanto 2008, Colbert, Adkins et al. 2010, Al-Mubaraki and Busler 2013).

Incubators, for example, boast high survival rates among their startup tenants, measured as the percentage of tenants that graduated, and Lewis (2001) finds that the majority (~84%) of tenants remain in the vicinity of the incubator upon graduation. High density thus allows continued collaborations between firms that becomes routinized thereby making a cluster self-sustaining (Hoang and Antoncic 2003). It has also been found that proximity will stimulate communication and scientific exchange of ideas (Allen, Raz et al. 2009). Other common reasons why a business moves into an incubator include to minimize initial operating costs, and for a supportive environment offering space and business services (Markley and McNamara 1995, Ruland 2013).

Researchers and practitioners have published case studies and best practices for the management of these regions, but verifying their economic impact remains elusive (Udell 1990, Van Geenhuizen and Soetanto 2008, Albort-Morant and Ribeiro-Soriano 2016). Incubators rarely track their tenants once they graduate from the incubator and into a less supportive environment (Lewis 2001, Avnimelech, Schwartz et al. 2007), and a cohort study by Schwartz (2013) even reveals that startup survival is statistically significantly better among companies that never participated in an incubator. Among clusters, Ruland (2013) finds that the profitability of smaller firms tends to be considerably lower than for firms that opt not to join clusters.

The above evidence seems to contradict social capital theory and knowledge management models of entrepreneurship, which predict that the sharing of tacit knowledge is crucial to startup success (Nonaka, Toyama et al. 2000, Cope, Jack et al. 2007, Hughes, Ireland et al. 2007). Sorenson, Rivkin and Flemings's study (2006) on the role of social proximity on knowledge diffusion found that with simple knowledge firms near and far perform similarly, but socially proximate firms have the greatest advantage as knowledge becomes more complex. Singh (2005) finds that knowledge flows are particularly strong within the same region. Davidsson and Honig (2003) found that being a member of a business network had a positive effect on financial milestones (first sale and profitability), but did not account for density. Feldman and Zoller (2012) find that startup success and its contribution to the regional economy are impacted more by dealmakers than by the density of startups or investors.

A study by Stuart and Sorenson of the bio-tech industry (2003) suggests clustering plays an essential role for entrepreneurs in high-tech industries because social relationships allow them to obtain the resources needed to create a new firm. However they find that although entrepreneurs may prefer to establish new firms in geographic concentrations, the most productive new ventures are not located in regional clusters, speculating that the benefits from clustering may disappear as the geographic reach of firm's social network expands.

In their study on incubator typologies, Hughes, Ireland, and Morgan (2007) may explain this inconsistency in startup performance when they argue that “Firms’ destiny lies in the hands of their combinations of strategic networking activities, and incubation outcomes do not occur because of their mere presence in an incubator.” The managed services that incubators and clusters provide their tenants typically consist of basic office resources (e.g., office space, receptionist, and Internet) and human capital training (e.g., seminars on intellectual property protection and finance) (Lumpkin and Ireland 1988), none of which provide the tacit knowledge that contributes to a startup’s competitive advantage. While social capital may be available, it may be difficult for entrepreneurs to locate the right individual in a complex network (Tötterman and Sten 2005), or not be used due to fear of knowledge spillover to competitors (Ruland 2013).

Region administrators and policy makers thus face a quality versus quantity dilemma, summarized by Isenberg (2012) “In focusing entrepreneurship policy almost exclusively on startups we are favoring quantity of startup at the expense of quality of scale-up.” On one hand, the high concentration of startups in business incubators, parks, and clusters seems to cost-effectively yield a favorable regional economic impact; Lewis (2001) calculates the cost to the public sector for each startup job created in an incubator is only between $3K and $12K. On the other hand, the failure rate of startups graduating from assisted environments like incubators is higher. Fahey and Prusak point out in their critique of the knowledge management discipline that the second most common error committed by researchers and practitioners is “emphasizing knowledge stock to the detriment of knowledge flow” (Fahey and Prusak 1998, pg. 266). If the accumulation of tacit knowledge through sharing is important to startup survival, region administrators and policy makers may be making the same mistake.

We attempt to shed empirical light on this dilemma by analyzing the relationships between the geographical density of business clusters, the sharing of asymmetric information, and firm survival in longitudinally-tracked startups, controlling for the nature (high tech versus low tech) of the density. We use the qualifier "asymmetric" to distinguish information that has a significant positive impact on the firm's competitive advantage from other types of information offered at incubators and clusters such as that from human capital training.

2. Methods and Data

Density

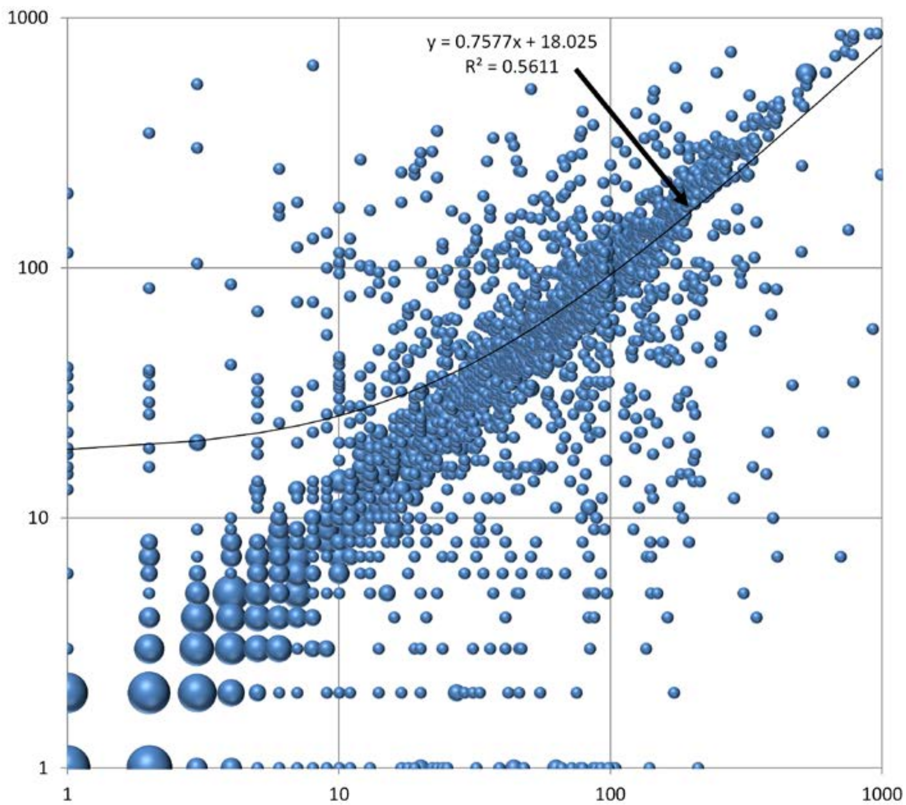
This study uses the confidential version of the longitudinal Kauffman Firm Survey (KFS) of 4928 companies founded in 2004 and surveyed annually from 2004 to 2011 (Robb and Farhat 2013). The KFS dataset is augmented with the County Business Patterns (CBP) dataset of the United States Census Bureau such that for every firm in the KFS we obtain the number of companies in its ZIP code with the same North American Industry Classification System (NAICS) sector code. We use this count as a measure of the geographical density of the startup's industry at its location. Note that the number of firms in the startup's ZIP code, without filtering by NAICS code, would not yield an industry-specific density measure.

The CBP information is available for every year from 2004 to 2010. Spatial variation in density is very high (Table 1). For example, every year at least 75 startups are the only establishments of their two-digit NAICS code in their ZIP code (density=1), and several startups are one of over 1000 establishments in their same ZIP code with the same two-digit NAICS code. Temporal variation in density is also significant. The density at the locations of KFS startups surviving to

2011 is on average similar to that where they initially formed, but the fit about the trend line has a low R^2 of 0.56 (Figure 1). This also indicates that density be a time-varying covariate in the startup survival model, as opposed to a fixed covariate.

Year	Surviving KFS Startups	Density Mean	Density Std. Dev.	Density Min	Density Max
2004	4,830	76.7	104.7	1	1409
2005	4,257	73.9	101.6	1	1416
2006	3,747	76.4	101.9	1	1421
2007	3,345	78.1	101.6	1	1508
2008	2,931	76.7	104.1	1	1481
2009	2,659	75.7	105.4	1	1488
2010	2,342	77.1	106.3	1	1469

Table 1. Descriptive statistics of startup density (number of firms in the same ZIP code as the startup and with similar NAICS sector code).



(Circle area is proportional to number of companies with those densities in 2004 and 2011)

Figure 1. Density at firms' locations: 2004 vs 2011

Density varies significantly by NAICS sector code (Table 2). For example, agriculture, forestry, fishing and hunting industries (NAICS sector 11), traditionally rural, have the lowest density. The zip codes of 98 KFS startups (2.0% of participants), including the three in the Public Administration sector, did not match CBP records and are excluded from density analyses. The KFS asked if participants considered their startup to be a high-tech firm. The sector IDs of the 649 participants that consider themselves to be high-tech are presented in Table 3.

# of Startups	Average Density	NAICS Sector ID	NAICS Sector Title
1203	128.8	54	Professional, Scientific, and Technical Services
243	114.4	45	Retail Trade (General Merchandise, Non-Store Retail)
283	114.2	44	Retail Trade (Market Specific Retail)
121	111.3	62	Health Care and Social Assistance
186	73.7	52	Finance and Insurance
98	68.2	72	Accommodation and Food Services
390	67.4	23	Construction
454	64.6	81	Other Services (except Public Administration)
219	58.9	42	Wholesale Trade
518	42.0	33	Manufacturing (Mechanical, Electrical)
151	39.2	32	Manufacturing (Lumber, Chemicals, Pharma)
177	38.1	53	Real Estate Rental and Leasing
360	37.8	56	Admin, Support, Waste Mgmt & Remediation Services
51	35.0	31	Manufacturing (Food, Beverage, Textile, Apparel
102	23.9	48	Transportation and Warehousing
5	21.5	21	Mining
164	20.3	51	Information
10	20.2	49	Transportation and Warehousing (Messenger & Storage)
105	12.2	71	Arts, Entertainment, and Recreation
29	9.9	61	Educational Services
10	4.4	55	Management of Companies and Enterprises
6	3.0	22	Utilities
40	2.3	11	Agriculture, Forestry, Fishing and Hunting
3	N/A	92	Public Administration

Table 2. Average density of companies by startup NAICS sector code (2004)

# of High-Tech Startups in Sector	Average High-Tech Density	NAICS Sector ID	NAICS Sector Title
399	133.9	54	Professional, Scientific, and Technical Services
174	41.2	33	Manufacturing (Mechanical, Electrical)
38	28.4	32	Manufacturing (Lumber, Chemicals, Pharma)
38	22.9	51	Information

Table 3. Average density of companies by high-tech startup NAICS sector code (2004)

Collaboration

We measure a startup's use of social capital by whether or not its founder believes that collaborations with other companies, universities, or government labs improved its competitive advantage. The KFS records each class of collaboration starting in the 2007 survey (Farhat and Robb 2014). This data does not describe the nature of the firm's network in detail, such as the topology of strong and weak ties (Greve and Salaff 2003, Pirolo and Presutti 2010), other than classifying collaborative partners into three categories. However, network information may not be necessary if the self-reported claim that collaboration impacted the firm's competitive advantage is trustworthy.

Startups report asymmetric collaboration activity all five years, with roughly 60% fewer collaborations in 2007 than in 2011 (Table 4); when measured as a percentage of surviving (and reporting) companies, collaborations are relatively consistent over this time period. This cross-sectional analysis, however, does not distinguish between many startups collaborating at different years, or few companies collaborating consistently. If the former, a startup survival model would use collaboration as time-varying covariates; if the latter, the model would use collaboration as a fixed covariate. Thus, we need to look at the startups' patterns of collaboration activity before selecting a model.

Year	Surviving Startups	Startups Collaborating with:					
		Companies		Universities		Gov. Labs	
2007	2915	434	14.9%	124	4.3%	49	1.7%
2008	2606	415	15.9%	89	3.4%	41	1.6%
2009	2408	366	15.2%	94	3.9%	41	1.7%
2010	2126	288	13.5%	80	3.8%	38	1.8%
2011	2007	257	12.8%	70	3.5%	32	1.6%

Table 4. Collaboration activity (as percentage of surviving startups)

Patterns of Collab with Company	Count	Patterns of Collab with University	Count	Patterns of Collab with Government	Count
000001	168	000001	61	000001	28
000010	133	000100	31	000010	17
000100	101	001000	30	001000	17
000011	66	000010	29	010000	17
001000	65	010000	27	000100	14
010000	59	000011	19	000011	4
000111	27	011111	11	000111	4
001100	25	001100	8	011110	4
000101	24	000110	7	000101	3
000110	22	000101	6	011100	3
001111	22	000111	6	001010	2
010100	22	011100	6	001011	2
011000	21	011000	5	001100	2
001110	20	001001	4	001110	2
011111	18	010100	4	001111	2
010001	17	010111	4	010101	2
011110	17	011101	4	000110	1
011100	16	001010	2	001001	1
001001	15	001110	2	010100	1
001011	14	001111	2	010110	1
⋮	⋮	⋮	⋮	⋮	⋮
011001	3	011110	1	011111	1
Total:	981	Total:	279	Total:	131

Table 5. Patterns of collaboration (consecutive digits indicate collaboration in years 2007 through 2011)

Collaboration activity can be represented as a five digit binary dummy variable, with the least significant digit being "1" of the company collaborated in 2007, the digit to the left being "1" if the company collaborated in 2008, and so forth with the most significant digit being "1" if the company collaborated in 2011. For example, the pattern 00101 indicates the company collaborated in 2007 and 2009 and did not collaborate in 2008, 2010, nor 2011. Table 5 presents the most frequent patterns of collaboration with the three types of collaborative partners (the pattern 00000 is excluded). The column "Count" indicates the number of KFS startups that exhibited that pattern of collaboration. Of the 4928 startups in the KFS, 981 collaborated at least one year with another business, 279 collaborated at least one year with a university, and 131 collaborated at least one year with a government laboratory. These numbers are more than double those of Table 4, indicating that a startup's asymmetric collaboration activity varies from year to year; this conclusion is also apparent from the five digit patterns themselves, and indicates the use a survival model with time-varying covariates.

Event History Analysis

Startup survival is commonly described as exponentially decreasing, i.e., a risk function that is constant over time. We thus fit startup survival to an exponential parametric model because startup survival is commonly described as exponentially decreasing with time, and because this model permits straightforward analysis of the effect of covariates on company survival.

Each panel of the KFS records the state each firm as (1) refused to participate at the current time, (2) previously stopped operations permanently, (3) stopped operations at the current time, (4) merged or sold at the current time, (5) temporarily stopped operations at the current time, or (6) continues to operate. Of these six states, only the third is considered a death event. A firm in the second state would have been labelled as being in the third state at some previous time in the survey. A merger or sale of a company is a negotiated exit strategy, which we do not consider to be a death event. Firms in states 1, 5, or 6 in 2011 are considered right censored.

We use Stata v14.1 to analyze the long-format multiply 5-times imputed version of the KFS dataset merged with CBP ZIP and NAICS code data (from which density is computed). The imputed version reduces the effects of missing values and produces in a five-fold count of firms (Farhat and Robb 2014). A life table model is first conducted to visualize the relationship between survival and social capital. A parametric exponential model of startup survival is then conducted to evaluate the relationships between survival, density, and social capital; this type of model was selected for the ease in which the model coefficients can be interpreted.

3. Results

A life table analysis confirms that collaboration improves the survival rate of startups (Table 6). Moreover, companies that collaborate with more than one type of collaborative partner (companies, universities, or government labs) have improved survival. To visualize this disparity in survival, Figure 2 plots the survival as a percentage of companies alive in 2007 (the year that KFS begins to collect information on collaboration), distinguishing by the number of types of collaborative partners. This does not distinguish between the number of collaborations with partners of the same type.

Interval	Beginning Total	Deaths	Lost	Survival	Standard Error	95% Confidence Interval	
				No Collaboration			
2004	17016	1818	0	0.8932	0.0024	0.8884	0.8977
2005	15198	1698	0	0.7934	0.0031	0.7872	0.7994
2006	13500	1344	0	0.7144	0.0035	0.7075	0.7211
2007	12156	1283	0	0.639	0.0037	0.6317	0.6462
2008	10873	884	0	0.587	0.0038	0.5796	0.5944
2009	9989	843	0	0.5375	0.0038	0.530	0.545
2010	9146	684	84	0.4971	0.0038	0.4896	0.5046
2011	8378	0	8378	0.4971	0.0038	0.4896	0.5046
				One Type of Collaboration			
2007	1536	127	0	0.9173	0.0070	0.9024	0.930
2008	1409	100	0	0.8522	0.0091	0.8335	0.869
2009	1309	51	0	0.819	0.0098	0.7988	0.8374
2010	1258	78	0	0.7682	0.0108	0.7463	0.7885
2011	1180	0	1180	0.7682	0.0108	0.7463	0.7885
				Two Types of Collaboration			
2007	232	12	0	0.9483	0.0145	0.9107	0.9703
2009	220	24	0	0.8448	0.0238	0.7915	0.8855
2010	196	24	0	0.7414	0.0287	0.6799	0.7928
2011	172	0	172	0.7414	0.0287	0.6799	0.7928
				Three Types of Collaboration			
2007	56	6	0	0.8929	0.0413	0.777	0.9504
2011	50	0	50	0.8929	0.0413	0.777	0.9504

Table 6. Life Table of KFS Startup Survival

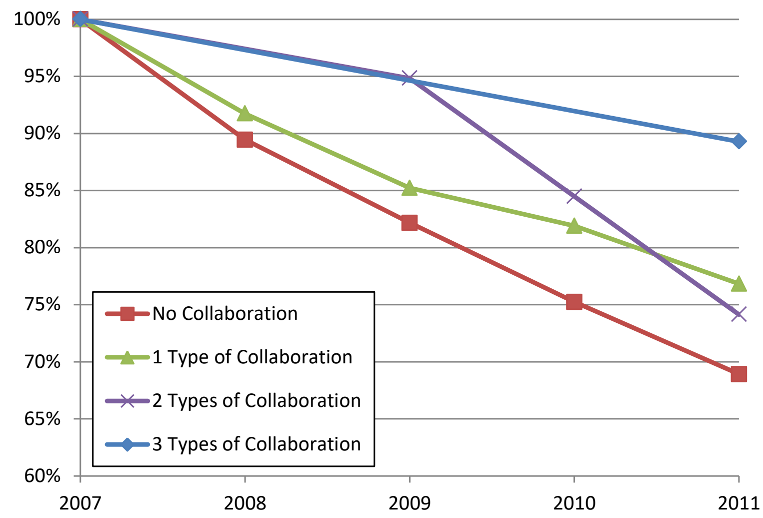


Figure 2. Startup Survival (relative to companies in business in 2007)

We fit an exponential parametric model to the KFS startup death events, using as time-varying covariates the number of types of collaborations (0, 1, 2, or 3) for each company for each year this is measured by the KFS, and the market-specific firm density for each year this is reported (and linked to the KFS) by the Census Bureau. The parametric model is a good fit (Table 7) and confirms the statistical significance (at the 1% level) of the relationship between improved survivability and collaboration. It also indicates that high-tech firms benefit from collaboration more than low-tech firms (at the 0.5% level). Density has a small and statistically insignificant impact on startup survival.

No. of subjects = 72,453	Number of observations = 96,737
No. of failures = 214,965	Time at risk = 2166956.056
Log pseudolikelihood =	-495583.15
Wald chi2(3) = 15.90	Prob > chi2 = 0.0012

	Coefficient	Std. Error	z	P> I z I	95% Conf. Interval	
Collaboration	-.3424199	.131373	-2.61	0.009	-.5999063	-.0849335
Density	.0002763	.0003196	0.86	0.387	-.0003501	.0009028
High-tech	-.2858886	.1024622	-2.79	0.005	-.4867109	-.0850663
α_0	-2.294634	.0388202	-59.11	0.000	-2.37072	-2.218548

Table 7. Parametric model of startup survival

Setting the exponential survivor function

$$G(t) = e^{-at} = e^{-te^{\alpha_0}} \qquad \textbf{Equation 1.}$$

to $G(\bar{t}) = 0.5$ and solving for $\bar{t}$ gives a median startup survival time of 6.88 years. The impact of a change in covariate A_j on the transition rate $r(t)$ of the exponential survivor function is

$$\Delta r = (e^{\alpha_j})^{\Delta A_j} - 1 \qquad \textbf{Equation 2.}$$

where α_j is the covariate's coefficient (Blossfeld, Golsch et al. 2012). The change in the transition rate (i.e., the risk of failing that year) by a one unit change in covariate A_j reduces to

$$\Delta r = e^{\alpha_j} - 1. \qquad \textbf{Equation 3.}$$

Changing from no collaborations to one type reduces the risk of failure by $e^{-0.3424} - 1$= -29%, to two types by $(e^{-0.3424})^2 - 1$= -50%, and to three types by by $(e^{-0.3424})^3 - 1$= -64%. Holding collaboration constant, high-tech startups have $e^{-0.2859} - 1$= -25% less risk of failure than low-tech startups.

4. Discussion, Limitations, and Future Work

Our findings suggest that clustering and the availability of social capital do not necessarily lead to startup survival. This seems to confirm Stuart and Sorenson's finding that while clusters offer conditions conducive to new venture creation, they do not support their growth. Our study also finds that the availability of social capital does not have a significant relationship with the utilization of social capital. In other words, while clustering can offer numerous benefits, it does not guarantee that firms will actually capitalize on those benefits.

A limitation of this work is that the exponential model applies a constant transition rate to startup risk, i.e., startup survival exponentially decreases. However, incubators and clusters endeavor to provide tenant firms with an environment that is more supportive than “the real world.” If so, the risk function associated with startup survival would be lower while the startup inhabits such an environment, and increases when the startup leaves it. Future work will investigate the use of a Weibull accelerated failure time distribution to model startup risk because it is the simplest parametric model that can represent monotonically and asymptotically increasing risk over time.

5. Conclusions and Implications

This work contributes to incubator and cluster best practices by highlighting the importance of social capital sharing to startup success, and by suggesting that cluster administrators promote collaboration within their critical masses. It also proposes the use of collaboration as a predictor of startup success, which might disambiguate the conflicting effectiveness of clusters and incubators reported in the literature. In contrast to building human capital with subject matter experts, which is expensive and difficult to scale, many business incubators have already built the social capital stock desired by their tenants. Our study indicates that incubator administrators should proceed directly to promoting its utilization in a distributed fashion, leveraging the startup density it has amassed.

Implications for Entrepreneurship Education

Entrepreneurship curriculum is often organized around traditional disciplines borrowed from management or the scientific/technical fields from which the students originate. Group projects notwithstanding, these disciplines involve predominantly solitary activities, and entrepreneurship curriculum rarely emphasizes the importance of tacit knowledge and the building of social capital for opportunity discovery and risk mitigation. This research addresses ongoing discussion in the literature differentiating high quality entrepreneurship from just high quantities of entrepreneurs. Instructors need to develop experiential activities that obligate students to develop social capital. The nature of social capital networks should also be taught. For example, Pirolo and Presutti (2010) find that "too much close and strong social networking can negatively influence the ability of the start-ups to reach high levels of innovation performance during their entire life cycle." Such activities should transcend the classroom and force the student to engage a broader ecosystem, just as incubator/cluster tenants must transcend training courses and engage the critical mass of their environment.

6. References

Al-Mubaraki, H. M. and M. Busler (2013). "Business Incubation as an Economic Development Strategy: A Literature Review." International Journal of Management **30**(1 Part 2): 362-372.

Albort-Morant, G. and D. Ribeiro-Soriano (2016). "A bibliometric analysis of international impact of business incubators." Journal of Business Research **69**(5): 1775-1779.

Allen, T., O. Raz and P. Gloor (2009). Does Geographic Clustering Still Benefit High Tech New Ventures? The Case of the Cambridge/Boston Biotech Cluster, MIT ESD-WP-2009-01 working paper.

Avnimelech, G., D. Schwartz and R. Bar-El (2007). "Entrepreneurial high-tech cluster development: Israel's experience with venture capital and technological incubators." European planning studies **15**(9): 1181-1198.

Blossfeld, H.-P., K. Golsch and G. Rohwer (2012). Event history analysis with Stata, Psychology Press.

Colbert, C., D. Adkins, C. Wolfe and K. Lapan (2010). Best Practices in Action - Guidelines for Implementing First-Class Business Incubation Programs, National Business Incubator Association.

Cope, J., S. Jack and M. B. Rose (2007). "Social Capital and Entrepreneurship An Introduction." International Small Business Journal **25**(3): 213-219.

Davidsson, P. and B. Honig (2003). "The role of social and human capital among nascent entrepreneurs." Journal of Business Venturing **18**(3): 301-331.

Fahey, L. and L. Prusak (1998). "The eleven deadliest sins of knowledge management." California management review **40**(3): 265-276.

Farhat, J. B. and A. Robb (2014). "Applied Survey Data Analysis Using Stata: The Kauffman Firm Survey Data." Available at SSRN 2477217.

Feldman, M. and T. D. Zoller (2012). "Dealmakers in Place: Social Capital Connections in Regional Entrepreneurial Economies." Regional Studies **46**(1): 23-37.

Gilbert, B. A., P. P. McDougall and D. B. Audretsch (2008). "Clusters, knowledge spillovers and new venture performance: An empirical examination." Journal of business venturing **23**(4): 405-422.

Greve, A. and J. W. Salaff (2003). "Social networks and entrepreneurship." Entrepreneurship theory and practice **28**(1): 1-22.

Hoang, H. and B. Antoncic (2003). "Network-based research in entrepreneurship: A critical review." Journal of business venturing **18**(2): 165-187.

Hughes, M., R. D. Ireland and R. E. Morgan (2007). "Stimulating Dynamic Value: Social Capital and Business Incubation as a Pathway to Competitive Success." Long Range Planning **40**(2): 154-177.

Isenberg, D. (2012). "Focus Entrepreneurship Policy on Scale-Up, Not Start-Up." Harvard Business Review **21**.

Lewis, D. A. (2001). Does technology incubation work?: A critical review, Economic Development Administration, US Department of Commerce Washington, DC.

Lumpkin, J. R. and R. D. Ireland (1988). "Screening Practices of New Business Incubators: The Evaluation of Critical Success Factors." American Journal of Small Business **12**(4): 59-81.

Markley, D. M. and K. T. McNamara (1995). "Economic and fiscal impacts of a business incubator." Economic Development Quarterly **9**(3): 273-278.

Nonaka, I., R. Toyama and N. Konno (2000). "SECI, Ba and leadership: a unified model of dynamic knowledge creation." Long range planning **33**(1): 5-34.

Pirolo, L. and M. Presutti (2010). "The Impact of Social Capital on the Start-ups' Performance Growth." Journal of Small Business Management **48**(2): 197-227.

Porter, M. E. (2000). "Location, competition, and economic development: Local clusters in a global economy." Economic development quarterly **14**(1): 15-34.

Robb, A. and J. Farhat (2013). An Overview of the Kauffman Firm Survey: Results from 2011 Business Activities, Ewing Marion Kauffman Foundation.

Ruland, W. (2013). "Does Cluster Membership Enhance Financial Performance?" I-Business **5**(1): 1.

Saxenian, A. (1996). "Inside-Out: Regional Networks and Industrial Adaptation in Silicon Valley and Route 128." Cityscape **2**(2): 41-60.

Schwartz, M. (2013). "A control group study of incubators' impact to promote firm survival." The Journal of Technology Transfer **38**(3): 302-331.

Singh, J. (2005). "Collaborative networks as determinants of knowledge diffusion patterns." Management science **51**(5): 756-770.

Sorenson, O., J. W. Rivkin and L. Fleming (2006). "Complexity, networks and knowledge flow." Research policy **35**(7): 994-1017.

Stuart, T. and O. Sorenson (2003). "The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms." Research policy **32**(2): 229-253.

Tötterman, H. and J. Sten (2005). "Start-ups business incubation and social capital." International small business journal **23**(5): 487-511.

Udell, G. G. (1990). "Are business incubators really creating new jobs by creating new business and new products." Journal of Product Innovation Management **7**(2): 108-122.

Van Geenhuizen, M. and D. P. Soetanto (2008). "Science Parks: what they are and how they need to be evaluated." International Journal of Foresight and Innovation Policy **4**(1-2): 90-111.