The Power of Proximity: The Impact of Proximity Between Early-Stage Investors and Universities

Ole Peters and Louisa Heiduk
HHL Leipzig Graduate School of Management, Germany

ole.peters@hhl.de
louisa.heiduk@hhl.de

Abstract: Early-stage investors and universities are crucial stakeholders in entrepreneurial ecosystems, yet their combined impact remains underexplored. This paper examines how the proximity between early-stage investors and universities affects the founding rate and success of affiliated startups. The analysis utilizes data from the Crunchbase 500 list for Germany. Findings indicate a positive correlation between the proximity of early-stage investors and universities with higher success rates and founding rates of affiliated startups. However, the results show varying dynamics and partial statistical significance, suggesting different implications for small versus large universities. Should these tendencies be confirmed with a more extensive dataset, the findings could have practical implications for early-stage investors and universities, tailored to their size.

Keywords: Venture capital, Start-ups, Entrepreneurial ecosystem, Start-up founding rate, Start-up success rate, Investor start-up proximity

1. Introduction

Start-ups backed by venture capitalists (VCs) significantly contribute more to economic growth than those without VC support (Gompers et al. 2020; Samila & Sørensen 2011; Sørensen 2007). VCs invest in start-ups primarily due to high return expectations. Because start-ups typically exhibit asymmetric returns, VCs aim to identify outliers within their portfolios that can provide substantial returns (Cochrane 2005). Although VCs evaluate factors like team, product, market environment, and strategy, they often face significant information asymmetry compared to the founders (Gompers et al. 2020; Kaplan & Strömberg 2004). To mitigate this, VCs syndicate and exchange information within their networks (Alexy et al., 2012; Ljungqvist et al., 2005). Universities are crucial to the entrepreneurial ecosystem, providing research for new technologies and attracting and educating the human capital necessary for launching businesses (Padilla-Meléndez et al. 2021; Rodríguez-Gulías et al., 2016). However, there is a scarcity of studies examining the interrelation between universities and VCs. Existing literature, such as works by Atkinson, Croce et al., and Kremer et al. (1994; 2014; 2022), focus on university-affiliated or university-managed VC funds, while Cai et al. (2016) concentrate on VC-backed founders and executives from the US with MBAs from top-ranked business schools. There is a notable gap in the literature concerning the impact of proximity between universities and early-stage investors on start-up founding rates and success. This study aims to fill this gap by. The proposed hypotheses are:

> ***H1**: Investors that have closer relationships with universities are investing in more successful start-ups.*
>
> ***H2**: Universities with closer relationships with early-stage investors are associated with more successful start-ups founded by their former students.*
>
> ***H3**: Universities with closer relationships with early-stage investors have a relatively higher founding rate of start-ups among their former students.*

These hypotheses were chosen to explore the multi-dimensional impacts of proximity, including its role in facilitating knowledge transfer, fostering trust, and enhancing coordination between investors and academic institutions. By testing these hypotheses, we aim to provide insights into how localized interactions within entrepreneurial ecosystems can foster innovation and growth.

2. Background and Context

2.1 Impact of Early-Stage Investors

Funding is critical for start-up success (Cantamessa et al. 2018). Different types of investors, including family and friends (F&Fs), business angels, crowd investors, and VCs, contribute varied resources such as financial capital and social capital. F&Fs often provide initial seed funding and emotional support, which is crucial for nascent entrepreneurs (Berger et al. 2020). Their involvement can reduce the perceived risk of entrepreneurship and provide a safety net. However, their lack of experience in start-up investments can lead to complex ownership structures and administrative challenges (Bessière et al. 2020). Business angels offer both financial capital and valuable networks, often investing locally and actively participating in the start-up's growth (Kelly 2007; Mason et al. 2016). They typically have entrepreneurial experience and provide mentorship, strategic advice, and access to their networks. Studies have shown mixed results on the impact of business angels, with some indicating significant positive effects on start-up success (Fili & Grünberg 2016; Kerr et al. 2014), while others find no substantial contribution (Cavallo et al. 2019). Crowd investments have gained importance, allowing start-ups to raise funds from a large number of small investors. This method is particularly effective for consumer products, as it combines capital raising with market validation and feedback (Brown et al. 2018). However, crowd-funded start-ups may struggle to attract traditional VC funding due to perceived lower quality and regulatory complexities (Mochkabadi & Volkmann 2020). Despite these challenges, crowd investors can provide a quick infusion of capital and initial customer engagement, critical for early-stage validation and growth (Mollick 2014). VCs are crucial in providing substantial financial resources and expertise. They perform rigorous due diligence and contribute to the start-up's strategic direction, leveraging extensive networks to facilitate growth (Gompers et al. 2020). VCs prioritize factors such as the founding team, business model, market potential, and product innovation when making investment decisions (Kaplan & Strömberg 2004). Their involvement often signals quality to other investors and stakeholders, thereby enhancing the start-up's credibility and access to additional resources (Barry et al. 1990).

2.2 Impact of Universities

Universities play a pivotal role in entrepreneurial ecosystems by generating knowledge, fostering innovation, and nurturing human capital (Audretsch 2014). The economic impact of universities has evolved from primarily political and social contributions to significant economic drivers, particularly through technology transfer and start-up support (Romer 1986). Universities contribute to start-up ecosystems by providing research, attracting and educating talent, and fostering an entrepreneurial mindset (Padilla-Meléndez et al. 2021). Knowledge spillovers from university research can lead to the development of new technologies and business models (Audretsch et al. 2012). This spillover effect is facilitated through collaborations, publications, and the mobility of skilled graduates who transfer knowledge to the industry (Acs et al. 2009). High-ranking universities with strong entrepreneurship programs tend to produce more successful founders (Cai et al. 2016). Entrepreneurship education provides students with the skills and knowledge needed to start and manage new ventures. These programs often include practical components such as business plan competitions, mentorship from experienced entrepreneurs, and access to incubation facilities (Franklin et al. 2001). Universities also facilitate start-up formation through technology transfer offices, incubators, and proof-of-concept centers, providing essential resources and support to nascent entrepreneurs (Audretsch 2014). These support structures help bridge the gap between academic research and commercial application, increasing the likelihood of successful start-up formation (Gaspar 2009). The concept of "entrepreneurial universities" highlights the shift towards a more proactive role in commercializing research and fostering start-up ecosystems (Harrison & Leitch 2010).

2.3 Proximity of Investors and Universites

The intersection of early-stage investors and universities is critical in the formation of university spin-offs. Existing literature evaluates the performance of university-led VCs (Atkinson, 1994; Croce et al., 2014; Kremer et al. 2022) and universities' roles in spin-offs (Alexy et al., 2012; Hayter, 2013; Lerner, 2004; Padilla-Meléndez et al. 2021; Wright et al., 2006). Additionally, factors such as coordination (Hayter, 2016b) and faculty entrepreneurial behavior (Hossinger et al., 2020) are significant, with venture capital being crucial to spin-off creation and success (Munari & Toschi 2011; Smith & Bagchi-Sen 2012). Notably, university-led VCs exhibit lower investment exit rates (Kremer et al., 2022). Knowledge spillover theory, where universities act as knowledge intermediaries and VCs as capital intermediaries, further elucidates the dynamics (Acs et al. 2013; Hayter 2016). For instance, VC-backed university spin-offs have a 20-26% higher commercialization rate (Hayter 2013), consistent with other studies (Harrison & Leitch 2010; Samila & Sørensen 2010). Universities can enhance start-up support through strict admission criteria and initiatives like incubator programs and pitch events, which positively signal to investors and improve founding rates (Berger et al. 2020; Cai et al. 2016). Early-stage investors provide not only financial but also social capital, vital for start-up success. However, university spin-offs often face an equity gap as traditional investor types like friends and family are less available (Widding et al. 2009). The benefits of investor proximity to universities are debated. Some studies show that specialized networks or extensive diverse networks enhance investment performance (Alexy et al. 2012; Ljungqvist et al. 2005), while a mix of these networks does not (Alexy et al. 2012). Gompers et al. (2009) find that specialization and experience, rather than extensive networks, improve VC performance. Furthermore, VC-backed start-ups where the founder and VC executive share a business school background tend to be more successful (Cai et al. 2016).

3. Data and Methodology

3.1 Data Collection

The underlying data for this study was sourced from Welpe et al. (2021), who enhanced the Crunchbase 500 (cb) list by adding German universities of the founders. The cb list from December 2020 ranks 500 German start-ups based on criteria like the number of connections a profile has, the level of community engagement, funding events, news articles and acquisitions. An entity's rank is fluid and subject to rise and fall over time. Time-sensitive events such as product launches, funding events, leadership changes and news affect a company's Crunchbase rank (Crunchbase 2021). The ranking position is assumed to correlate with start-up success. The given data set is not without its limitations. First, the data has a strong success bias since the data set only considers the best-ranked start-ups, according to Crunchbase. At the same time, the measurement of success is not 100% transparent since it is based on the intransparent Crunchbase algorithm. It cannot be guaranteed that Crunchbase's ranking does not consider the educational background or the list of investors for their ranking. Alternative success measurements like IPO rate or failure rate are not suitable for the given list of start-ups due to the young age and recency of the analyzed start-ups (Gompers et al., 2009) and creation of job opportunities due to the different business models of the compared start-ups. From this list, 426 start-ups were identified with at least one founder who graduated from a German university. If founders studied at different universities, all were considered. University size was measured by the number of enrolled students as collected by Welpe et al. (2021). Ownership data were analyzed using the Amadeus database. Of the 426 start-ups, early-stage investor data were available for 401 start-ups. Early-stage is defined as an average of three years, encompassing periods from incubation/pre-seed to seed phase and seed phase to series A, typically lasting 12 to 24 months each (Cavallo et al. 2019). Dates of incorporation were verified through various online sources, including Germany's commercial register. The investor list included all shareholders, including founders who invested in other start-ups. For instance, a founder from one of the 401 start-ups investing in another start-up counted as two start-up investments.

3.2 Data Analysis

This paper uses data from the Crunchbase 500 list for German start-ups from December 2020, supplemented by the educational background of founders and the respective start-ups' early investors. Two proprietary proximity scores were calculated to quantify the relationships between universities and investors.

The proximity score PS(*Investor*) for an investor to universities has been calculated according to the following formula:

$$PS(Investor) = 1 - \sum_i \frac{U(i)}{i\,U}$$

Here, i denotes the number of investments the investor has with one university. U(i) denotes the number of universities which are affiliated with the investor i times. The proximity score is high for investors who invested in start-ups affiliated with fewer universities, but more often with the same universities. A score of 0 would mean that all of the invested start-ups are associated with different universities. A score of 1 would mean that the investor invested in an infinite number of start-ups at the same university. In short, the PS(*Investor*) proximity score measures how concentrated an investor's investments are within a few universities

Accordingly, the proximity score PS(*University*) for a university to investors is defined as follows:

$$PS(University) = 1 - \sum_i \frac{I(i)}{i\,I}$$

Here, i denotes the number of investments at one university from the same investor. I(i) denotes the number of investors which are affiliated with the university i times. The proximity score is high for universities who received many start-up investment from a low number of investors. A score of 0 would mean that each start-up from the university was funded by different investors. A score of 1 would mean that an infinite number of start-ups at the university were funded by only one investor. The proximity score is higher for universities with fewer affiliated investors but more affiliated investors that invested in more start-ups from this university. The score ranges between zero – no investor invested in two or more start-ups from this university – and one – all investors invested in two or more start-ups from this university. In short, the PS(*University*) proximity score measures how concentrated a university's investments are from a few investors.

3.3 Descriptive Statistics – Investors

The investor list was manually consolidated to identify related entities and individuals. The dataset comprised two tables. The first identified 237 investors with at least three investments in the 401 start-ups within three years post-incorporation, with 16 investors making ten or more investments. The second table included 86 universities affiliated with at least three start-ups, with 26 universities affiliated with ten or more start-ups. The investors have been filtered for those with at least three investments in the given data set to have more reliable proximity scores that would be otherwise highly influenced by the small number of investments and, therefore, associated universities. The considered investors have between three and 37 different investments in the data set. The distribution of the number of investments can be seen in Table 1 and is highly concentrated at the lower end, with 44% of the investors with only three investments in the given data set and 19% with four investments. More than 93% have less than ten investments.

Table 1: Frequencies of Variables in the Data Set Regarding the Investors

	Mean	Percentile 25	Median	Percentile 75	Std. Deviation
Number of investments	5	3	4	6	4
Average cb rank of investments	213.72	156.14	204.33	263.67	77.76
Proximity of investors to universities	.19	.00	.17	.30	.17
Proximity of investors to universities without zero scores	.28	.17	.25	.35	.13
Number of universities associated with investments - counted once	10	6	9	12	7

The scores are not normally distributed, with a high number of zero scores (Figure 1 (c)). The distribution of proximity scores larger than zero is almost perfectly normal (Figure 1 (d)). However, the large number of 78 investors with a proximity score of zero results in an uneven distribution (Figure 1 (c)), which demands the use of non-parametric statistics for the analysis. The last relevant variable in this data set is the number of universities an investor is associated with. This variable is lognormal distributed, which is why all subsequent calculations use this variable's natural logarithm (ln).

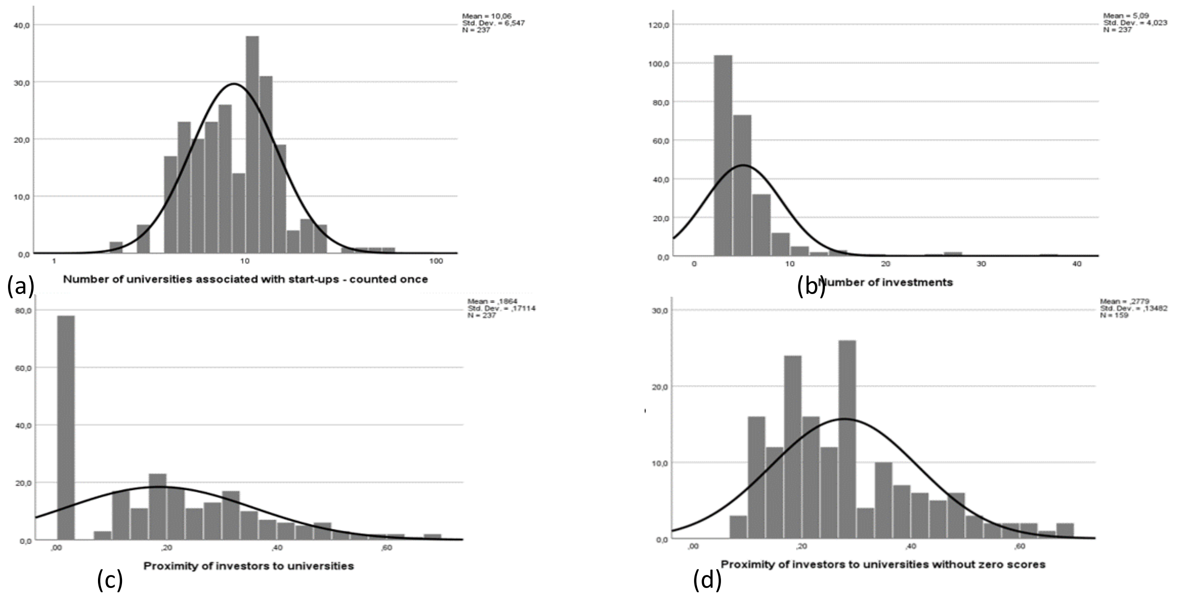

Figure 1: Histograms of Investor Related Variables

3.4 Descriptive Statistics – Universities

After filtering the data for universities with at least three start-ups in the data set, 86 universities are left to be analyzed. Those universities have a median of 17.952 students. The number of students is distributed close to a lognormal distribution; hence all subsequent calculations use the ln that shows a slight negative skew (see Figure 2 (a)). The same applies to the number of start-ups affiliated with a university. However, compared to the ln of the number of students, the ln of the number of start-ups has a strong positive skew due to the high number of universities with three and four start-ups in the data set (see Figure 2 (b)).

Table 1: Frequencies of Variables in the Data Set Regarding the Universities

	Mean	Percentile 25	Median	Percentile 75	Std. Deviation
Number of students	20.662	8.350	17.952	30.153	15.110
ln of number of students	9.54	9.03	9.80	10.31	1.06
cb Startups per 100 students	.1685	.0231	.0390	.0694	.5267
ln of cb Start-ups per 100 students	1.58	.83	1.36	1.93	1.20
Number of startups	10	4	6	11	11
ln of number of startups	1.92	1.39	1.79	2.40	.78
Average cb rank of startups	266.14	225.23	267.28	303.53	58.73
Proximity to investors	.0309	.0000	.0000	.0410	.0552
Number of investors associated with this university	115	39	68	122	141

The number of students and the number of start-ups affiliated with a university in the given data set is deviating a lot which is why also the cb start-ups per 100 students deviate heavily across the universities. Again, the natural logarithm is used, which shows weak positive skew (see Figure 2 (c)).

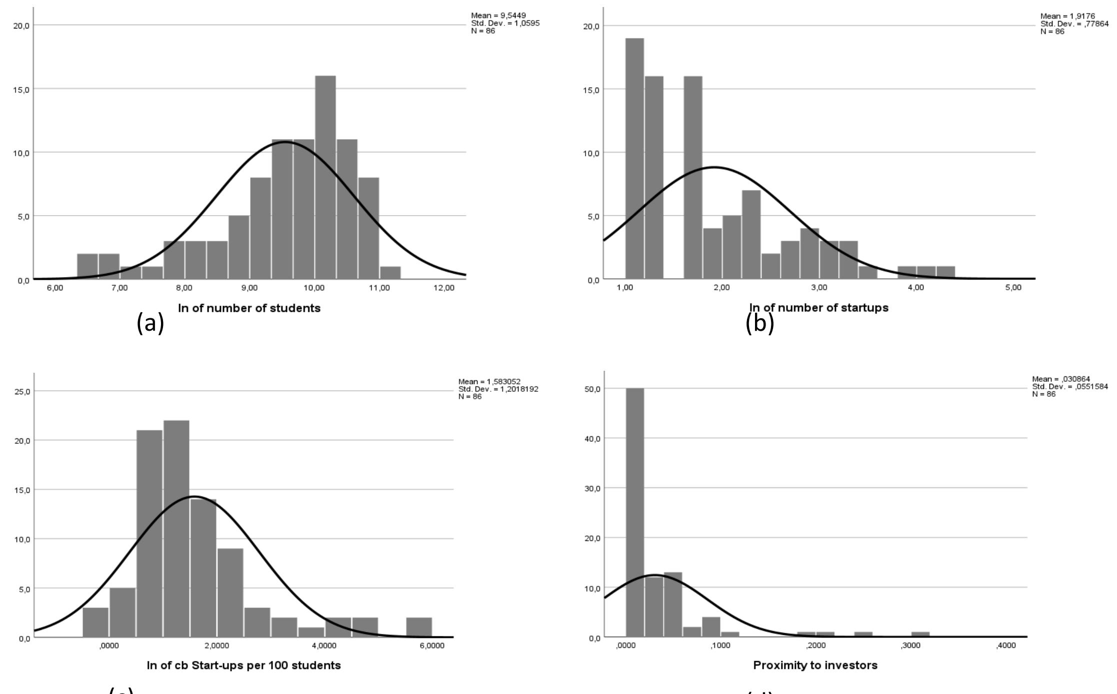

Figure 2: Histograms of University Related Variables

4. Results

The first hypothesis (H1) posits that investors with higher proximity scores are more likely to invest in successful start-ups. This analysis was conducted using the Kruskal-Wallis test, to account for the non-normal distribution of data. As Table 1 indicates most investors tend to invest in start-ups from a limited number of universities. This pattern suggests that certain investors may have a preference or specialization. In addition, Table 3 categorizes investors based on their proximity scores and the number of investments they have made. It can be deducted that investors with higher proximity scores frequently invest in start-ups from the same universities, suggesting a focused investment strategy.

Table 2: Distribution of Classed Investors According to their Proximity Scores

			Proximity of investors to universities				
			Count	Count (%)	Mean	Median	Std. Deviation
Proximity of investors to universities (classed)	No proximity		78	32.9%	.00	.00	.00
	Low proximity		19	8%	.11	.12	.02
	Medium proximity		45	19%	.18	.17	.03
	High proximity		47	19.8%	.27	.28	.03
	Very high proximity		48	20.3%	.45	.43	.10

However, the K-test results show that there is no statistically significant correlation between higher proximity scores and the success rates of start-ups (*p = 0.515*). While there is a non-significant tendency for investors with higher proximity scores to invest in more successful start-ups, the correlation is not strong enough to be statistically significant (Table 4). Even though the mean ranks have the right direction for the stated hypothesis, the null hypothesis must be retained due to the high scattering of the cb rank average. The findings suggest that proximity is one of many factors influencing start-up success, and further research is needed to explore additional variables that might play a more decisive role. The pairwise comparison of the proximity scores of successful and less successful start-ups additionally aids the tendency for higher proximity scores to be associated with more successful start-ups. However, the statistical analysis confirms that this tendency is not significant, reinforcing the conclusion that proximity alone is not a decisive factor in start-up success.

Table 3: K-test Results for H1

Ranks

	Proximity of investors to universities (classed)	N	Mean Rank
Average cb rank of investments	No proximity	78	128.07
	Low proximity	19	123.42
	Medium proximity	45	117.73
	High proximity	47	116.73
	Very high proximity	48	105.92
	Total	237	

Test Statistics[a,b,c]

	Average cb rank of investments
Kruskal-Wallis H	3.259
df	4
Asymp. Sig.	.515

a. Kruskal Wallis Test
b. Grouping Variable: Proximity of investors to universities (classed)
c. Some or all exact significances cannot be computed because there is insufficient memory.

The second hypothesis (H2) posits that universities with higher proximity scores are associated with more successful start-ups. Table 5 categorizes universities based on their proximity scores and the number of start-ups they have produced. Higher proximity scores indicate that universities frequently produce start-ups that receive investments from the same investors. The categorization helps in understanding the concentration and focus of start-up investments at different universities.

Table 4: Distribution of Classed Universities According to their Proximity Score

		Proximity to investors				
		Count	Count (%)	Mean	Median	Std. Deviation
Proximity to investors (classed)	No proximity	45	52.3%	.0000	.0000	.0000
	Low proximity	6	7.0%	.0163	.0163	.0045
	Medium proximity	18	20.9%	.0362	.0380	.0073
	High proximity	17	19.8%	.1120	.0931	.0794

The K-test results (see Table 6) show a statistically significant correlation between higher proximity scores and the success rates of start-ups (*p = 0.065*). This finding suggests that universities with higher proximity scores tend to produce more successful start-ups, indicating the importance of close relationships between universities and investors. The null hypothesis can be cautiously rejected. A subsequently conducted pairwise comparison between the different types of universities grouped by their degree of proximity (no proximity to high proximity) showed a significant difference between the groups with the highest proximity and the ones with no proximity (see Figure 3), supporting the statement that universities with high proximity to investors are associated with more successful start-ups on average than universities with no proximity to investors.

Table 5: K-test Results for H2

Ranks

	Proximity to investors (classed)	N	Mean Rank
Average cb rank of startups	No proximity	45	48.02
	Low proximity	6	49.83
	Medium proximity	18	43.33
	High proximity	17	29.47
	Total	86	

Test Statistics[a,b,c]

	Average cb rank of startups
Kruskal-Wallis H	7.229
df	3
Asymp. Sig.	.065

a. Kruskal Wallis Test
b. Grouping Variable: Proximity to investors (classed)
c. Some or all exact significances cannot be computed because there is insufficient memory.

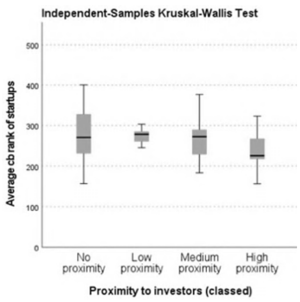

Figure 3: Pairwise Comparison of H2

The third hypothesis (H3) posits that universities with closer relationships with early-stage investors have a relatively higher founding rate of start-ups. Again, this hypothesis was tested using the Kruskal-Wallis test, due to the non-normal distribution of the data. For H3, the groups based on the proximity of universities to investors are compared based on the relative founding rate. The relative founding rate is captured in the variable cb start-ups per 100 students that divids the count of start-ups in the given data set per university by the number of students the university had in December of 2020. The results of the K-test show an asymptotic significance of 0.003 (see Table 7), which indicates that the null hypothesis can be rejected. In other words, the groups of universities with different proximity to investors show statistically significant differences in relative founding rates. Of particular interest is the pairwise comparison, which reveals a statistically significant difference between universities with no proximity to investors and those with high proximity (see Table 7). Although other pairwise comparisons exhibit a similar trend—especially the group with high proximity—they do not reach statistical significance. This lack of significance could be attributed to the relatively small sample size of universities in the dataset.

Table 6: K-test Results for H3

Ranks

	Proximity to investors (classed)	N	Mean Rank
cb Startups per 100 students	No proximity	45	36.20
	Low proximity	6	38.00
	Medium proximity	18	45.94
	High proximity	17	62.18
	Total	86	

Test Statistics[a,b,c]

	cb Startups per 100 students
Kruskal-Wallis H	13.820
df	3
Asymp. Sig.	.003

a. Kruskal Wallis Test
b. Grouping Variable: Proximity to investors (classed)
c. Some or all exact significances cannot be computed because there is insufficient memory.

Table 7: Pairwise Comparisons of Proximity to investors (classed)

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
o proximity-Low proximity	-1.800	10.852	-.166	.868	1.000
No proximity-Medium proximity	-9.744	6.964	-1.399	.162	.970
No proximity-High proximity	-25.976	7.109	-3.654	<.001	.002
Low proximity-Medium proximity	-7.944	11.771	-.675	.500	1.000

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
Low proximity-High proximity	-24.176	11.857	-2.039	.041	.249
Medium proximity-High proximity	-16.232	8.445	-1.922	.055	.328
Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050. a. Significance values have been adjusted by the Bonferroni correction for multiple tests.					

To accurately interpret this result, one must consider the potential confounding effect of the number of start-ups affiliated with a university. This variable likely influences both the proximity score and the cb start-ups per 100 students score. Specifically, a higher number of start-ups at a university will naturally elevate the cb start-ups per 100 students score. Concurrently, a greater number of start-ups tends to attract more investors, thereby increasing the proximity score between universities and investors (see Figure 4 and Figure 5). To address this potential confounder, we conducted a comparison of the proximity groups with respect to the natural logarithm of the number of start-ups associated with each university. This K-test resulted in even higher explanatory values for the group with no proximity (Table 7). At the same time, it does not show the strong tendency for the universities with high proximity to investors compared to the cb start-ups per 100 students (Table 8).

Table 8: Pairwise Comparisons of Proximity to investors (classed)

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
No proximity-Medium proximity	-26.000	6.894	-3.771	<.001	.001
No proximity-Low proximity	-27.806	10.744	-2.588	.010	.058
No proximity-High proximity	-40.507	7.038	-5.756	<.001	.000
Medium proximity-Low proximity	1.806	11.654	.155	.877	1.000
Medium proximity-High proximity	-14.507	8.361	-1.735	.083	.496
Low proximity-High proximity	-12.701	11.739	-1.082	.279	1.000
Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050. a. . Significance values have been adjusted by the Bonferroni correction for multiple tests					

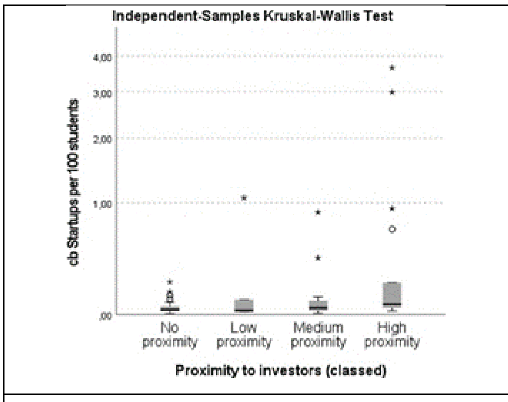

Figure 4: Pairwise Comparison for H3

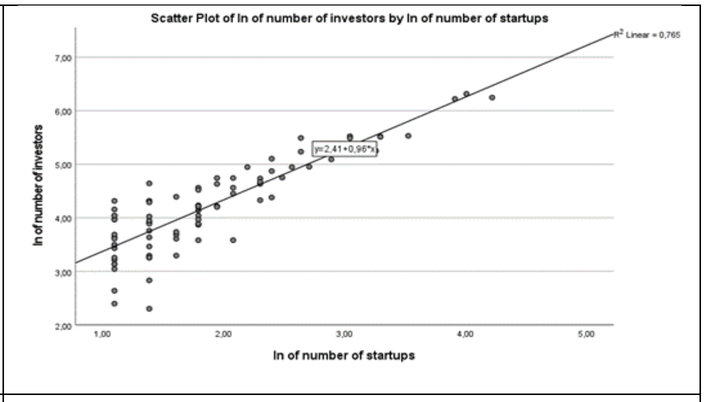

Figure 5: Scatterplot of ln of Number of Startups and ln of Number of Investors Associated with this University

This mixed result permits various interpretations. For instance, despite the increased sensitivity of the proximity score for universities with fewer start-ups and consequently fewer investors, universities with a very low number of start-ups do not exhibit high proximity scores to investors. This may be because universities with few start-ups are less attractive to investors, or because the lack of investor focus leads to fewer start-ups being founded by students at these universities. This contradictory interpretation underscores a significant limitation of this finding, namely that it does not establish causality.

5. Discussion

As presented in "4. Results" in detail, the test for H1 does not show statistically significant correlation between higher proximity scores of investors to universities and the success rates of their start-up investments, but they do hint towards the right tendency. For H2, the test results in a statistically significant correlation between higher proximity scores of universities to investors and the success rates of start-ups from former students of these universities. For H3, the tests show mixed results with statistically significant explanatory values for universities with no proximity to investors having lower founding rates of start-ups among their former students." The findings suggest practical implications for both universities and investors. Universities should foster relationships with early-stage investors to enhance start-up success and founding rates. For investors, focusing on universities with strong entrepreneurial programs could yield better investment outcomes. Universities can enhance their entrepreneurial ecosystems by providing resources and support to facilitate start-up formation. This includes creating incubators, hosting pitch events, and connecting students with potential investors. Investors, in turn, can benefit from focusing on universities with strong entrepreneurial cultures and support systems, which are likely to produce more successful start-ups. The findings align with existing literature on the importance of networks and social capital in entrepreneurial ecosystems (Alexy et al. 2012; Gompers et al. 2020). Strong relationships between universities and investors can enhance the flow of information, resources, and support, leading to higher success rates for start-ups. The proximity score developed in this study provides a quantifiable measure of the relationship between universities and investors. Higher proximity scores indicate stronger relationships and higher levels of interaction, which can positively impact start-up success and founding rates. This score can be used as a benchmark for universities and investors to assess and improve their collaborative efforts.

6. Conclusion

This study underscores the importance of proximity between universities and early-stage investors in enhancing start-up ecosystems. The findings suggest that universities with strong relationships with investors tend to produce more successful start-ups and have higher founding rates. Future research should explore larger datasets and additional variables to confirm these findings. The limitations of this study include the focus on German start-ups and the use of the Crunchbase 500 ranking, which may introduce a success bias. Additionally, the proximity score is a simplified measure and may not capture all aspects of the relationships between universities and investors. Despite these limitations, the study provides valuable insights into the dynamics of entrepreneurial ecosystems and highlights the need for strong collaborations between universities and early-stage investors. Overall, fostering closer collaborations between universities and investors can significantly enhance the entrepreneurial ecosystem. Future research should aim to establish causality and expand the dataset for more comprehensive insights.

References

Acs, Z. J., Braunerhjelm, P., Audretsch, D. B., & Carlsson, B. (2009) 'The knowledge spillover theory of entrepreneurship', *Small Business Economics*, 32(1), pp. 15-30. DOI: 10.1007/s11187-008-9157-3.

Alexy, O., Block, J. H., Sandner, P. G., & Ter Wal, A. L. (2012) 'Social capital of venture capital investors and start-up funding', Small Business Economics, 39(4), pp. 835-851. DOI: 10.1007/s11187-011-9337-4.

Atkinson, S. H. (1994) 'University-affiliated venture capital funds', Health Affairs, 13(3), pp. 159–175. DOI: 10.1377/hlthaff.13.3.159.

Audretsch, D. B. (2014) 'From the entrepreneurial university to the university for the entrepreneurial society', Journal of Technology Transfer, 39(3), pp. 313-321. DOI: 10.1007/s10961-012-9288-1.

Audretsch, D. B., Hülsbeck, M., & Lehmann, E. E. (2012). ‚Regional competitiveness, university spillovers, and entrepreneurial activity', Small Business Economics, 39(3), 587–601. DOI: 10.1007/s11187-011-9332-9.

Barry, C., Muscarella, C. J., Peavy, J., & Vetsuypens, M. (1990) 'The role of venture capital in the creation of public companies: Evidence from the going-public process', Journal of Financial Economics, 27(2), pp. 447-471. DOI: 10.1016/0304-405X(90)90064-7.

Berger, M., Egeln, J., & Gottschalk, S. (2020), ‚Finanzierung von Unternehmensgründungen durch Privatinvestoren: Auswertungen und Analysen auf Basis des IAB/ZEW-Gründungspanels 2019', Mannheim.

Bessière, V., Stéphany, E., & Wirtz, P. (2020) 'Crowdfunding, business angels, and venture capital: An exploratory study of the concept of the funding trajectory', Venture Capital, 22(2), pp. 135-164. DOI: 10.1080/13691066.2019.1599188.

Brown, R., Mawson, S., & Mason, C. (2018) 'Myth-busting and entrepreneurship policy: The case of high growth firms', Entrepreneurship & Regional Development, 30(1-2), pp. 1-27. DOI: 10.1080/08985626.2017.1364787.

Cai, Y., Gantchev, N., & Sevilir, M. (2016), 'Business School Networks and VC-backed Startups' Kelley School of Business Research Paper No.(15-79). DOI: 10.2139/ssrn.2684572.

Cantamessa, M., Gatteschi, V., Perboli, G., & Rosano, M. (2018) 'Startups' road to failure', Sustainability, 10(7). DOI: 10.3390/su10072346.

Cavallo, A., Ghezzi, A., & Balocco, R. (2019) 'Entrepreneurial ecosystem research: Present debates and future directions', International Entrepreneurship and Management Journal, 15(4), pp. 1291-1321. DOI: 10.1007/s11365-018-0526-3.

Cochrane, J. H. (2005) 'The risk and return of venture capital', Journal of Financial Economics, 75(1), pp. 3–52. DOI: 10.1016/j.jfineco.2004.03.006.

Croce, A., Martí, J., & Murtinu, S. (2014) 'The impact of Venture Capital on the growth of European entrepreneurial firms: 'Screening'or 'value added'effect?', Journal of Business Venturing, 29(4), pp. 488-507. DOI: 10.1016/j.jbusvent.2012.06.001.

Fili, A., & Grünberg, D. (2016) 'Business angel post-investment activities: a multi-level review', Journal of Management & Governance, 20, pp. 89-114. DOI: 10.1007/s10997-014-9296-7.

Franklin, S. J., Wright, M., & Lockett, A. (2001) 'Academic and surrogate entrepreneurs in university spin-out companies', Journal of Technology Transfer, 26(1-2), pp. 127-141. DOI: 10.1023/A:1007896514609.

Gaspar, J. (2009) 'The role of universities in technology transfer'. In: Proceedings of the 2009 International Conference on Technology Management and Innovation.

Gompers, P. A., Gornall, W., Kaplan, S. N., & Strebulaev, I. A. (2020) 'How do venture capitalists make decisions?', Journal of Financial Economics, 135(2), pp. 169-190. DOI: 10.1016/j.jfineco.2019.06.011.

Harrison, R. T., & Leitch, C. M. (2010) 'Voodoo institution or entrepreneurial university? Spin-off companies, the entrepreneurial system and regional development in the UK', Regional Studies, 44(9), pp. 1241-1262. DOI: 10.1080/00343400903167912.

Hayter, C. S. (2013) 'Harnessing university entrepreneurship for economic growth: Factors of success among university spin-offs', Economic Development Quarterly, 27(1), pp. 18-28. DOI: 10.1177/0891242412471845.

Hayter, C. S. (2016). Constraining entrepreneurial development: A knowledge-based view of social networks among academic entrepreneurs. *Research Policy*, *45*(2), 475–490. DOI: 10.1016/j.respol.2015.11.003.

Kaplan, S. N., & Strömberg, P. (2004) 'Characteristics, contracts, and actions: Evidence from venture capitalist analyses', Journal of Finance, 59(4), pp. 2177-2210. DOI: 10.1111/j.1540-6261.2004.00696.x.

Kelly, P. (2007) 'Business angel contracts: The influence of context', Venture Capital, 9(4), pp. 307-333. DOI: 10.1080/1369106032000141940

Kerr, W. R., Lerner, J., & Schoar, A. (2014) 'The consequences of entrepreneurial finance: Evidence from angel financings', Review of Financial Studies, 27(1), pp. 20-55. DOI: 10.1093/rfs/hhr098.

Kremer, M., Achleitner, A.-K., & Braun, R. (2022) 'University VC– Promise and Pitfalls', SSRN Online Publication. DOI: 10.2139/ssrn.4016443.

Lerner, J. (2004) 'The university and the start-up: Lessons from the past two decades', Journal of Technology Transfer, 29(3-4), pp. 355-370.

Ljungqvist, A., Hochberg, Y., & Lu, Y. (2005) 'Whom You Know Matters: Venture Capital Networks', SSRN Online Publication. DOI: 10.2139/ssrn.687211.

Mason, C., Botelho, T., & Harrison, R. (2016) 'Transformation of the business angel market', *Venture Capital*, *18*(4), 321–344. DOI: 10.1080/13691066.2016.1229470.

Mochkabadi, K., & Volkmann, C. K. (2020) 'Equity crowdfunding: A systematic review of the literature', Small Business Economics, 54(1), pp. 75-118. DOI: 10.1007/s11187-018-0081-x.

Mollick, E. (2014) 'The dynamics of crowdfunding: An exploratory study', Journal of Business Venturing, 29(1), pp. 1-16. DOI: 10.1016/j.jbusvent.2013.06.005.

Padilla-Meléndez, A., Del Aguila-Obra, A., & Diánez-González, J. (2021) 'The emerging role of universities in developing a knowledge-intensive entrepreneurial ecosystem: The case of Andalusia', Journal of Technology Transfer, 46(4), pp. 1175-1198.

Rodríguez-Gulías, M. J., Rodeiro-Pazos, D., & Fernández-López, S. (2016) 'Impact of Venture Capital on the growth of university spin-offs'. In: Peris-Ortiz, M., Ferreira, J. J., Farinha, L., & Fernandes, N. O. (Eds.), Innovation, technology, and knowledge management, Springer International Publishing, pp. 169-183. DOI: 10.1007/978-3-319-29677-7_11.

Romer, P. M. (1986) 'Increasing returns and long-run growth', Journal of Political Economy, 94(5), pp. 1002-1037. DOI: 10.1086/261420.

Samila, S., & Sørensen, O. (2010) 'Venture capital as a catalyst to commercialization', Research Policy, 39(10), pp. 1348–1360. DOI: 10.2138/ssrn.1533787.

Samila, S., & Sørensen, O. (2011) 'Venture capital, entrepreneurship, and economic growth', Review of Economics and Statistics, 93(1), pp. 338-349. DOI: 10.1162/REST_a_00066.

Sørensen, M. (2007) 'How Smart Is Smart Money? A Two-Sided Matching Model of Venture Capital', The Journal of Finance, 62(6), pp. 2725–2762. DOI: 10.1111/j.1540-6261.2007.01291.x.

Welpe, I., Abdel-Massih, M., Uhlemann, K., Bielmeier, S., Horvath, B., & Heidegger, L. (2021). *Benchmarking der Entrepreneurship Performance deutscher Hochschulen*. Munich. TUM - Chair of Strategy and Organization.

Widding, L. O., Mathisen, M. T., & Madsen, O. (2009) 'University-affiliated Venture Capital funds: funding of University Spin-Off companies', International Journal of Technology Transfer and Commercialisation, *8*(3). DOI: 10.1504/IJTTC.2009.024387.

Wright, M., Lockett, A., Clarysse, B., & Binks, M. (2006) 'University spin-out companies and venture capital', Research Policy, 35(4), pp. 481-501. DOI: 10.1016/j.respol.2006.01.005.