Comparing University Spin-Off performance

Financial performance comparison between University Spin-Offs (USOs) and Deep-tech organizations in the Dutch ecosystem

Radboud Universiteit

Master Thesis

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Preface

Five years at the Radboud University, Nijmegen, have led me to the completion of the master thesis. It marks the final step towards completing the master Innovation & Entrepreneurship and graduating. Writing the master thesis has been challenging, educational and rewarding, and it would not have been possible without the guidance and expertise of my supervisor, Dr. Ir. Nanne Migchels. I am thankful for his support the past months. I would also like to thank my girlfriend, family and friends. They are an immeasurable force that enable me to thrive forwards in live, and for that I am grateful without limitation.

I hope you enjoy reading my research!

Tom Beek

Roermond, June, 2025

Abstract

University spin-offs (USOs) are known for they economic and social development, yet systematic comparisons with other high-technology start-ups remain underdeveloped. Using a database consisting of 1874 Dutch organizations this research aimed to analyse the difference between USOs and Deep-tech organizations (non-USO New Technology Based Firms) across four financial performance dimensions: survival, revenue growth, employee growth and IPO/M&A achievement. Mediation analysis tested whether founding team size, external funding, and innovativeness explained a performance difference. The results showed USO outperform Deep-tech organizations in terms of survival (14% more likely to survive) and employee growth (5.5% faster growth). These advantages are partially mediated by greater access to external funding (56% more external funding). The remaining difference in performance can potentially be explained by positive effects USOs experience as a result of the university support they receive. However, USOs are less likely to achieve an IPO or M&A compared to Deep-tech organizations, although this effect partially diminishes once funding disparities are accounted for (50% less likely to achieve an IPO/M&A). Founding management team size and number of patents did not significantly mediate performance. This research enables USO entrepreneurs and support programs to increase the success of USOs and guides external funding allocation as a result of the improved the understanding of financial performance per organization type.

Key words: University spin-offs, Deep-tech organizations, Financial performance, External funding, Dutch start-ups

Content

Introduction

University spin-offs (USOs) are the commercialization of newly discovered academic knowledge. They have proven to be crucial for economic and social development (Shane, 2004; Wood, 2011). Consequently, there has been a rising interest in USOs from academia and practitioners in recent years (Bigliardi et al., 2013; Mathisen & Rasmussen, 2019; Miranda et al., 2018).

USOs are a subgroup of New Technology Based Firms (NTBFs) (Storey & Tether, 1998). NTBFs are firms established within knowledge-intensive industries and characterised by high levels of R&D expenses. NTBFs typically are independent firms or corporate spin-offs (CSOs) based on the transfer of knowledge from a parent firm (Fryges & Wright, 2014). This research will draw a comparison with non-USO Deep-tech organizations, a type of independent or corporately founded NTBFs which are known for knowledge intensive and disruptive innovations (De la Tour et al., 2017). USOs and Deep-tech organizations frequently introduce competing technologies resulting in a competition for market share and growth (Zahra et al., 2007). While USOs and Deep-tech organizations share characteristics in terms of technological advancement and scientific commercialization (De la Tour et al., 2017), they have different characteristics which leads to an interesting comparison between the organization types. USOs are characterized by a close university relationships, large founding management teams, high levels of external funding and exceptionally high levels of innovativeness (Bolzani et al., 2021; Moray & Clarysse, 2005; Ortín-Ángel & Vendrell-Herrero, 2014; Wright et al., 2006). These factors could potentially lead to, or explain, different financial performance between the two types of organizations. The overlap in knowledge transfer and the competition for market share rises interest in the comparison between USOs and Deep-tech organizations. Achieving an in depth understanding whether the origin of a startup, academic versus corporate or independent, affects its financial performance is crucial. Especially in these highly competitive, uncertain markets where early-stage firms struggle for survival and growth. If the characteristics of USOs lead to systematically different outcomes, this has major implications for innovation policy, public funding strategies, and university entrepreneurship support systems.

Previous studies on this topic have led to conflicting results (Hossinger et al., 2020; Mathisen & Rasmussen, 2019). A notable challenge in earlier research is the variety of USO definitions used in terms of individual, institutional and technological characteristics (Bonardo et al., 2011; Toole & Czarnitzki, 2007; Wennberg et al., 2011; Zhang, 2009). In order to mitigate this challenge, this research utilizes the inclusive definition of Mathisen & Rasmussen (2019), which aims to include the complete spectrum of USOs, as opposed to constraining the scope to specific subgroup.

Moreover, comparing USOs to suitable other firms has proven to be challenging. Some researchers have compared the financial performance of USOs with all other firms (Zhang, 2009) or with CSOs in particular (Wennberg et al., 2011). However, these comparison organizations differ significantly from USOs in key areas such as technology commercialization and knowledge intensity. Unlike USOs, the companies used for comparison in the previous studies are not characterised by high R&D expenditure and a high dependence on trained technical personnel. These distinctive features of USOs introduce unique risks that can affect financial outcomes, making previous comparisons potentially misleading.

Additionally, the data utilised in previous comparison research is more than 15 years old. This is particularly problematic when considering the significant rise in the number of USOs created in the past two decades (Prokop, 2023), the improved understanding of factors that influence USO performance (Mathisen & Rasmussen, 2019) and increase in the support from governments (Grimaldi et al., 2011). These factors have resulted in a body of USOs which might be performing significantly better, that have not yet been investigated in comparison research.

These challenges encountered in previous research lead to the importance of new research in this field. New research should be conducted in order to get an improved understanding of USO performance and the influencing characteristics, leading to better practice and enhancement strategies.

A number of financial performance measures are used in this research to test the influence of USO characteristics on their performance. These metrics are survival, revenue growth, employee growth and Initial Public Offering (IPO) or Merger and Acquisition (M&A) achievement. These measurements are evaluated as strong indicators and have therefore been used in a great quantity of previous performance evaluation research (Bonardo et al., 2010; Czarnitzki et al., 2014; Ensley & Hmieleski, 2005; Salvador, 2011; Wennberg et al., 2011; Zhang, 2009).

This research aims to contribute to the current body of literature on technology transfer by comparing the financial performance of USOs and Deep-tech organizations using recent data from the Netherlands. Additionally, this research aims to identify which USO characteristics significantly influence their performance compared to Deep-tech organizations. This leads to the following research question:

> RQ: *Which characteristics of USOs influence their financial performance compared to Deep-tech organizations in the Dutch startup ecosystem?*

By conducting an analysis of USO performance compared to Deep-tech organizations using a Dutch perspective, this research aims to contribute academically, socially and practically. Previous research has revealed that 75% of the European USOs don’t survive beyond six years after initiation (Mustar et al., 2008). This is of particular concern, as it reduces the economic and social benefits these organizations could otherwise contribute. It is crucial to increase the understanding of these firms, as it enables practitioners, universities and governments to enhance USO impact. This research aims to fill in a significant gap in the current body of literature by navigating the pitfalls previous researchers have identified and using a newer database, ultimately improving the understanding of USO performance.

Additionally, USOs are characterized by their social contribution concerning job creation, workforce development and knowledge transfer to industry (Miranda et al., 2018; Wood, 2011). A more profound comprehension of USO performance could assist these organizations in their growth and survival, enhancing the societal benefits they generate.

Finally, this research aims to contribute practically in the field of funding allocation. When considering USOs as an investment opportunity, governments, universities and external investors stand to benefit from a solid understanding of how USOs compare to other potential investments. This enhanced understanding could lead to improved funding allocation and increased investment results for these entities, which ultimately improves economic and social development.

Literature review

USO and Deep-tech definition

In order to achieve an improved understanding of the financial performance of USOs compared to Deep-tech organizations it is important to clearly define these concepts. Mathisen & Rasmussen (2019) stress the importance of having a clear theoretical rational for how the investigated samples differ in a comparative research. It is for this reason crucial to define these concepts precisely.

A spin-off is a separate legal entity aimed at commercializing knowledge that was developed by a previously established entity (parent organization) (Roberts & Wainer, 1968; Zahra et al., 2007). In the case of a USO, academic knowledge is commercialized. USOs are a phenomenon known for almost 40 years (Kenney, 1986) and represent a majority of the start-ups in industries like biotech (Bonardo et al., 2010). They are considered valuable firms for transferring new technology to their respective industries (Rasmussen et al., 2006; Walter et al., 2006). They have proven to provide economic and social development through dissemination of new technology and commercialization of otherwise undeveloped research (Clausen & Rasmussen, 2013; Shane, 2004). When defining the term USOs, this research uses the inclusive definition from Mathisen & Rasmussen (2019, p. 6):

> *'A USO is a new venture commercializing research results and scientific knowledge form a university and Public Research Institutions (PRIs)'*

USOs are a subgroup of NTBFs, which are organizations characterized by high levels of R&D expenses, activities in knowledge-intensive fields and employment of highly educated personnel (Storey & Tether, 1998). In this research, a comparison will be made with non-USO Deep-tech organizations, which are independent or corporately founded NTBFs. Deep-tech organizations are innovative and scientifically driven organizations by definition, and are known for their disruptive impact in various industries (De la Tour et al., 2017). The overlap in characteristics between USOs and Deep-tech organizations makes Deep-tech organizations a useful point of comparison for understanding and explaining the difference in financial performance of USOs compared to other firms. However, it is important to note crucial differences in characteristics between the organization types. This research focuses on the following areas of difference: founding management team size, external funding, innovativeness and university relationship. The potential for these characteristics to influence, or provide an explanation for, disparities in financial performance between USOs and Deep-tech organizations is a subject that requires further investigation.

Financial performance metrics

To evaluate the financial performance of USOs and Deep-tech organizations, four key metrics are analysed: survival, revenue growth, employment growth and IPO/M&A achievement. All these metrics have been validated in previous research and have proven to be valuable metrics for firm performance measurement (Bonardo et al., 2010; Wennberg et al., 2011; Zhang, 2009).

The interpretation of these metrics is most effectively put in the context of the financial lifecycle model (Berger & Udell, 1998). This model outlines how start-ups evolve through different stages in their development. Each performance metric is aligned with a specific stage in this lifecycle and reflects the firm's progress towards financial and operational maturity. By aligning the performance metrics with the lifecycle model, this research ensures that firm success is assessed not as a static concept, but as a dynamic outcome that evolves across stages of development, resulting in a richer comparison between USOs and Deep-tech organizations.

Survival is a fundamental prerequisite across all stages but is especially critical during the seed/startup phase, when firms are most vulnerable to failure due to limited resources, underdeveloped networks, and market uncertainty (Clarysse et al., 2007; Vohora et al., 2004). Survival reflects a firm's ability to overcome market uncertainty and adapt to initial market feedback (Zhang, 2009).

Revenue and employee growth are metrics of a firms' ability to scale and are therefore most relevant for the growth phase of the lifecycle. Revenue and employment are two measures of growth that are commonly used indicators for firm performance and are crucial measurements for tracking growth (Helm et al., 2018). These measurements reflects the ability of the organization to scale its operations.

Finally, the achievement of an IPO or M&A corresponds to the maturity and exit phases of the growth cycle. In the literature it is considered as a successful achievement for the spin-off as it typically signifies that a firm has reached a level of value and stability that attracts acquirers or allows it to go public (Shane, 2004; Zhang, 2009). An IPO or M&A is the event where parenting companies and VC realize a return on their investment.

Non-financial metrics such as profitability, market share, or time-to-market were not included due to their limited availability in standardized startup databases and their lower comparability across early-stage firms.

Hypothesis

Drawing on the resource-based view (Barney, 1991; Wernfelt, 1984) and social-capital theory (Bourdieu, 1986; Coleman, 1988), this research argues that USOs outperform deep-tech organizations because they combine four advantages: larger founding-management teams (H2), greater external funding (H3), stronger innovativeness (H4), and university relationships which provide unique advantages (H5). The first three mechanisms can be measured directly and will be analysed as mediating variables in this research. The fourth is unobservable in the used data and is expected to manifest as a residual effect of organisation type. This leads to the following hypothesis.

> *H1: USOs perform better than Deep-tech organizations in terms of a) survival, b) revenue growth, c) employee growth and d) IPO or M&A achievement*

Management teams

The founding management team is recognized as a critical determinant of start-up performance (McCarthy et al., 2023). USO are frequently established by founding teams rather than individual entrepreneurs for non-USO NTBFs (Rasmussen et al., 2011). Bigger founding management teams have proven to perform better compared to smaller founding teams (Eesley et al., 2014)

Survival

Larger founder teams are characterized by more diverse skills (Álvarez Pereira et al., 2024), which helps them to build a stronger market position by dividing responsibilities and managing uncertainties. This ultimately enables them to survive longer (Klepper, 2001). In contrast, start-ups with small teams may lack the managerial resilience and diversity in skills needed to survive the volatile startup environment.

Growth stage

Larger founding teams are known to possess a larger body of commercial and operational expertise which is crucial for the growth phase of a start-ups (Eesley et al., 2014). Additionally, smaller teams are less diverse in terms of background and perspectives which can result in a struggle to develop scalable business models or pursue market expansion, ultimately leading to lower growth levels (Ensley & Hmieleski, 2005).

IPO/M&A achievement

Broader management teams are able to acquire larger amounts of capital during an IPO as it signals higher certainty in future performance (Zimmerman, 2008). Teams lacking commercial leadership or exit experience may appear less credible to investors and acquirers, potentially reducing the likelihood of a successful exit.

While other factors like team cohesion, culture, team diversity and business expertise potentially influence startup success, they are not captured in large-scale quantitative databases. Because this research relies on quantitative data from startup databases, the focus is limited to founding management team size.

> *H2: USOs perform better compared to Deep-tech organizations in terms of a) survival, b) revenue growth, c) employee growth and d) IPO or M&A achievement, due to their larger founding management teams.*

External funding

USOs face barriers in terms of resources, networks and, most critically, funding (Clarysse et al., 2007; Vohora et al., 2004). Yet they are known to acquire high levels of external funding compared to non-USO NTBFs (Munari & Toschi, 2011), possibly as a result of growth potential and social impact. Access to external funding is vital for the survival, growth and exit stages of start-ups.

Survival

External funding is crucial for start-ups as it enables these organizations to overcome major resource limitations in their early stages (Vohora et al., 2004). External funding acts as a financial safety net, helping start-ups to overcome the “valley of death”. For this reason, high levels of external funding are associated with higher survival rates (Guo, 2024).

Growth stage

External funding, particularly venture capital, is a key driver of growth in terms of workforce and firm credibility enhancement (Davila et al., 2003). Additionally, previous research shows that increased grant funding raises the likelihood of receiving venture capital, ultimately boosting revenue (Howell, 2017). It is for this reason external funding is crucial for the growth stages of a start-up.

IPO/M&A achievement

Previous research has found that VC-backed firms experience a higher likelihood of exiting via an IPO (Chemmanur et al., 2009; Giot & Schwienbacher, 2007). The strong networks and market knowledge associated with external funding may be driving this trend.

These observations lead to the following hypothesis:

H3: USOs perform better compared to Deep-tech organizations in terms of a) survival, b) revenue growth, c) employee growth and d) IPO or M&A achievement, due to their greater access to external funding.

Innovativeness

Survival and growth stage

USOs acquire products form their parent organization with cutting-edge but immature technologies. Most spin-off products leave academia at TRL 1–3, long before commercial validation (Zahra et al., 2007). This results in heavy R&D cost during the early survival and growth phases and slower market entry compared to Deep-tech organizations.

IPO/M&A achievement

A substantial body of research has drawn attention to the high levels of innovation capabilities exhibited by USOs (Bonardo et al., 2010; Meoli et al., 2012; Toole & Czarnitzki, 2007). These innovative capabilities are the result of close proximity and collaborative partnerships with universities (Díez-Vial & Montoro-Sánchez, 2016; Lejpras, 2012). During the exit their strong IP possessions can become key assets that attract strategic acquirers or investors.

Therefore, while this dynamic has the potential to result in suboptimal figures during the early survival and growth stages of USOs, their superior innovation capabilities may become an advantage during an exit. This results in the following hypothesis:

H4: USOs perform worse compared to Deep-tech organizations in terms of a) survival, b) revenue growth and c) employee growth, but not in d) IPO or M&A achievement, due to higher levels of innovation

University relationship

A fundamental distinction between USOs and Deep-tech organizations is university affiliation and the corresponding support. The relationship between USOs and their parenting institution, often facilitated through Technology Transfer Offices (TTOs) or equivalents, has proven to offer many advantages for the USOs which may translate into superior performance throughout the organizations life cycle.

Survival

University affiliation increases early stage legitimacy, helping USOs overcome the liability of newness by signaling trustworthiness to first customers and partners (Harrison & Leitch, 2010; Salvador, 2011).

Independent deep-tech organizations have to establish credibility on their own which can be challenging.

Growth stage
Universities provide access to legal, marketing and HR services (Salvador, 2011) and facilitate knowledge transfer via formal and informal channels (Van Burg et al., 2013). These support services help formalize operations which leads to sustainable and efficient growth (Moray & Clarysse, 2005). Deep-tech organizations have to realize on their own, potentially at higher costs.

IPO/M&A achievement
Previous research shows the relationships with universities has a positive effect on the network of USOs (Harrison & Leitch, 2010; Rasmussen et al., 2011). Possessing a strong network with strategic alliances is crucial in order to increase attractiveness for acquisition and increase IPO valuation (Qi et al., 2015). While USOs experience advantages of the university relationship, deep-tech organizations have to create this network individually.

Because the advantages of university relationship are not quantified in the database but embedded in the business type variable, USOs are expected to outperform Deep-tech firms even after accounting for management team size, external funding and innovativeness.

> *H5: After controlling for mediating concepts, USOs still perform better than Deep-tech organizations in terms of a) survival, b) revenue growth, c) employee growth and d) IPO or M&A achievement*

Conceptual model

In summary, this research expects there is a difference in financial performance (survival, revenue growth, employee growth and IPO/M&A achievement) between the two organization types (H1). Additionally, this research expects that a part of this difference in financial performance can be explained by three mediating variables (founding management team size (H2), external funding (H3), innovativeness (H4)). However, it is not expected that all the financial performance difference between organizations can be explained by the mediating variables since the university relationship hypothesis (H5) is not quantitatively accounted for. This leads to the following conceptual model.

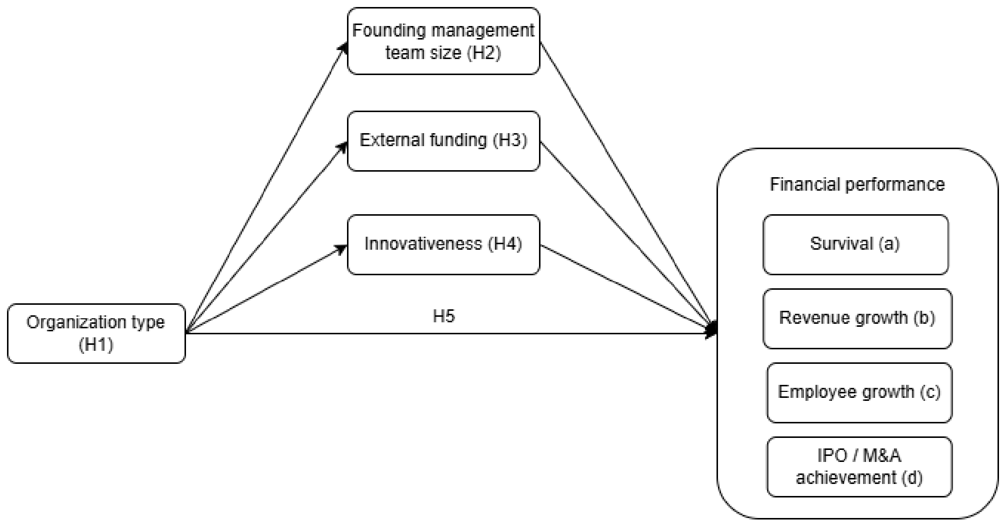

Figure 1: Conceptual model

Methodology

Research design

This research utilizes a quantitative, deductive research approach to compare the financial performance of USOs and Deep-tech organizations. A deductive approach is most suitable because it allows for hypothesis testing using a structured dataset (Hair et al., 2018). This research is comparative in nature, focussing on the differences in financial performance between USOs and Deep-tech organizations in the Dutch ecosystem.

Data collection

This research combined two databases acquired from Dealroom and Techleap, two reputable sources for startup data. Dealroom is an online database used by governments, VCs and founders which collects business specific data using a combination of machine learning, data engineering, manual verification and a network of ecosystems (*How Dealroom Collects Data*, n.d.). This database is used to filter out the Deep-tech organizations and their financial performance metrics. Techleap is a governmentally funded non-profit organization which aims to quantify and accelerate the Dutch technology ecosystem (*Who We Are » Techleap*, 2023). They have acquired an elaborate database of USOs as a result of previous collaborations in the Netherlands. This database is used to identify the USOs that will be evaluated in the comparison, as well as their associated financial performance metrics.

A partial overlap between the two databases was found. Organizations that were existent in both databases were removed from the Deep-tech database and retained in the USO database. This was chosen because these organizations do have university origin and are therefore most suitable for the USO database. The combined database contained a total 1874 organizations, consisting of 850 USOs and 1024 Deep-tech organizations (USOs are coded as 0 and Deep tech organizations as 1).

B.Type

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	850	45,4	45,4	45,4
	1	1024	54,6	54,6	100,0
	Total	1874	100,0	100,0	

Figure 2: Frequency table business type

In order to ensure the robustness of the comparison between USOs and Deep-tech organizations, this research includes all the available Dutch start-ups without limiting them to specific industries. This inclusion is necessary to obtain a sufficient sample size for the statistical tests. However, the sector classification has been maintained as a control variable. Startups operate under different dynamics depending on their sector which means that controlling for industry is essential in order to draw practically relevant conclusions from the findings. The biotech industry is particularly important because USOs are overrepresented in this sector (Bonardo et al., 2010) and because the RadboudUMC, the initiator of this research, is active in this sector. By accounting for sectoral differences, the study aims to provide more applicable insights to users of the research in different fields.

Variables

Concept	**Operationalization**	**Measurement**	**Variable type**
Organization type (B.Type)	Type of organization	USO (0), Deep-tech (1)	Dichotomous
Revenue growth* (R.Growth)	Compounded Annual Growth Rate (CAGR) of revenue	$(\frac{\text{Ending revenue}}{\text{Beginning revenue}})^{\frac{1}{\text{years}}} - 1$	Ratio
Employee growth* (E.Growth)	Compounded Annual Growth Rate (CAGR) of employee count	$(\frac{\text{Ending employees}}{\text{Beginning employees}})^{\frac{1}{\text{years}}} - 1$	Ratio
Survival** (Status)	Whether a firm is still active at the final date of the database**	Operational (1), closed (0)	Dichotomous
IPO / M&A achievement (IPO_M.A)	Whether a firm has gone public or been acquired	IPO/M&A achieved (1), not (0)	Dichotomous
Founding management team size (TeamSize)	Size of founding team	Number of founders	Ratio
External funding (T.Funding)	Total external funding received	Amount of external funding acquired (M €)	Ratio
Innovativeness (Patents)	Level of technological innovation	Number of granted patents	Ratio
Industry*** (Industry)	Primary sector of operation (clustered)***	Industry classification codes	Nominal

Table 1: Operationalization table

* The used period of analysis for the growth metrics was 2016 until 2025 since using recent data is a crucial criteria for this research. Since organizations founded before 2016 might have reached a mature phase, the growth variables are based on companies founded in 2016 or later. Employee growth was measured for the period 2016 to 2025, and revenue growth for 2016 to 2024.

** Operational and acquired companies were valued as Operational, low activity and closed were categorised as Closed

*** The primary industry classification of each company was used to avoid excessive fragmentation. These classifications were then grouped for statistical purposes (appendix A).

Ethical Considerations

It is fundamental to ensure ethical integrity in this research.

The data utilized in this research is all obtained through authorized access to maintain legal compliance. All the involved parties are aware of the exchange of information, aimed at achieving maximum transparency. The acquired data is carefully managed and never shared with third parties. The firms within the database will remain anonymous, thereby preventing the disclosure of sensitive financial or operational information.

As previously stated, Dealroom utilises AI and machine learning in their data collection and processing activities. It is for this reason that additional ethical considerations are acknowledged. The use of AI for data gathering and processing activities presents challenges in terms of selection bias and accuracy, resulting in potential misinformation (Safdar et al., 2020). However, Dealroom integrates a manual verification process where all acquired data is evaluated by their Intelligence Unit (*How Dealroom Collects Data*, n.d.). This drastically reduces the potential for algorithmic bias and increases the data accuracy.

Data analysis

Four separate mediation models were run, each rotating one of the four financial-performance metrics as the dependent variable. For the analysis of this research multiple regression analysis was utilised for continuous dependent variables and logistic regression analysis was utilised for dichotomous variables. The dataset was first harmonized by recoding key variables and merging the two original databases into a single analytical file. Descriptive checks (means, SDs, skewness, kurtosis) flagged non-normality for FundingM and Patents (appendix B). Subsequently, both were log-transformed with a +1 constant before further analysis, resulting in the following descriptive statistics.

Statistics

		B.Type	R.Growth	E.Growth	Status	IPO_M.A	TeamSize	LN_Fund	LN_Paten
N	Valid	1874	189	781	1866	1874	1165	1332	1874
	Missing	0	1685	1093	8	0	709	542	0
Mean		,55	,16192	,06001	,90	,08	1,88	,6898	,1623
Skewness		-,187	1,964	,576	-2,645	3,194	1,958	1,869	6,882
Std. Error of Skewness		,057	,177	,087	,057	,057	,072	,067	,057
Kurtosis		-1,967	10,350	1,635	5,002	8,213	6,499	3,125	65,922
Std. Error of Kurtosis		,113	,352	,175	,113	,113	,143	,134	,113

Figure 3: Descriptive statistics

Multicollinearity assumptions were tested for all models and showed acceptable results. Visual inspection of residual plots revealed no systematic curvature and adding polynomial terms failed to improve model fit for the multiple regression analysis. For the logistics regression a Funding × ln(Funding) interaction initially suggested mild non-linearity with Survival. However, due to the limited improvement of the model and the rise of multicollinearity issues the polynomial variable was not included and the linearity assumption was considered acceptable.

Mediation hypotheses were evaluated in IBM SPSS Statistics using PROCESS macro v4.0 (Model 4), estimated with either 1,000 or 5,000 bias-corrected bootstrap samples for logistic regression and multiple regression analysis respectively. In this PROCESS macro HC3 heteroscedasticity-consistent standard errors were utilised to safeguard against residual variance inequality. Because PROCESS does not compute the total effect for logistic regression, two separate logistic regression models were run without the mediating variables in order to compute the total effect.

Validity and reliability

While efforts are made to ensure high methodological rigor, it is important to reflect on the validity and the reliability of the research. The research is based on secondary data and limited to quantitative observable variables. This means that it may not capture all the qualitative nuances that could influence performance. This is a limitation to the external validity of this research. Additionally, the focus on the Dutch startup ecosystem limits the external validity and generalizability of this research, as other countries may have different cultures and practices which could influence performance.

Expanding the dataset with additional variables (e.g. managerial diversity) or employing additional research methods (e.g. interviews) could potentially deepen the analysis. However, the current approach is deliberately chosen as the most feasible within the scope and limitations of this research.

The chosen quantitative design allows for measurable and comparable insights across a large sample of organizations. The selected performance metrics and mediating variables have proven to be strong indicators for firm performance and influencers of start-up performance respectively. They include crucial elements of the scope of this research. All of this contributes to the strong internal validity and reliability of this research.

Analysis

The first round of analysis was done utilizing the complete conceptual model. However, when analyzing the results of these models the founding management team size variable showed interesting results. Initially, the founding management team size was included as one of three mediators based on prior research. However, during the analysis of the four mediation models, founding management team size did never show a significant indirect effect (For revenue growth 95% CI [-0.0153 0.0103], for employee growth 95% CI [-0.0021 0.0044], for survival 95% CI [-0.0772 0.0194] and for IPO/M&A achievement 95% CI [-0.0335 0.0751]; full results are in appendix C). Additionally, an independent samples t-test revealed no significant difference in founding management team size (t(137) = 1.37, p = .171) between the two organization types.

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
TeamSize	Equal variances assumed	,818	,366	1,370	1163	,085	,171	,089	,065	-,038	,215
	Equal variances not assumed			1,368	1144,400	,086	,172	,089	,065	-,038	,216

Figure 4: No significant difference in founding team size between two organization types

Since the PROCESS macro uses listwise deletion, meaning that cases with missing values on any of the variables involved in the model (independent, mediating, or dependent) are excluded from analysis, the inclusion of the variable reduced the clarity and robustness of the results. While the variable contributed no explanatory power and reduced the robustness of the results it was decided to remove the variable from the final models. This decision was made post hoc based on empirical findings. It is also for this reason that Hypothesis 2, that predicted that USOs perform better compared to Deep-tech organizations in terms of all performance metrics due to larger founding management teams, can be rejected.

The analysis presented in this chapter reflects only the two remaining mediators, being ‘external funding’ and ‘number of patents’. The four mediation models are shown in appendix D.

First staged path (a)

Prior to testing the full mediation models, the first-stage paths (a paths) were assessed to determine whether business type significantly predicted the two proposed mediators. Significant prediction of business type on a mediator can indicate as a first sign of a mediation effect.

While controlling for industry the analysis shows Deep-tech organizations received significantly less funding compared to USOs (B = −0.462, $p < .001$). When translating this to the original scale this means that USOs raise around 56% more external funding compared to similar Deep-tech organizations (because $e^{0.446} - 1 \approx 0.56$). Due to the +1 constant before transforming the external funding variable the approximation is most reliable for moderately large funding rounds. The model explained 7.6% of the variance in funding levels ($R^2 = .076$, weak to moderate). These results suggests that, although other factors potentially also influence external funding, organization type has significant influence. This supports the inclusion of LN_Fund as a meaningful mediator in the relationship between business type and performance outcomes.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,287[a]	,082	,076	1,03882

a. Predictors: (Constant), I_9, I_3, I_8, I_7, B.Type, I_2, I_4, I_6, I_5

Figure 5: Model summary, LN_Fund dependent variable

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,241	,151		1,597	,111		
	B.Type	-,446	,061	-,203	-7,344	<,001	,913	1,095
	I_2	,676	,176	,181	3,854	<,001	,314	3,188
	I_3	,060	,259	,007	,232	,816	,683	1,465
	I_4	,540	,175	,150	3,093	,002	,294	3,403
	I_5	,842	,158	,348	5,327	<,001	,163	6,134
	I_6	,859	,163	,312	5,278	<,001	,199	5,031
	I_7	,408	,193	,086	2,116	,035	,416	2,403
	I_8	,681	,206	,123	3,302	<,001	,498	2,007
	I_9	,802	,163	,293	4,920	<,001	,196	5,107

a. Dependent Variable: LN_Fund

Figure 6: Coefficients table, LN_Fund dependent variable

However, business type did not significantly predict LN_Paten once industry was controlled for (B = −0.018, p = .576). Instead, patenting activity appeared to be shaped more strongly by industry context, with organizations in Industry 5 (Health) showing significantly higher levels of patent output (B = 0.195, p = .019).

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	,100	,078		1,282	,200		
	B.Type	-,018	,032	-,013	-,559	,576	,919	1,088
	I_2	,049	,093	,021	,528	,598	,331	3,022
	I_3	-,093	,131	-,020	-,706	,480	,666	1,501
	I_4	-,008	,092	-,004	-,087	,931	,320	3,128
	I_5	,195	,083	,129	2,352	,019	,177	5,655
	I_6	,040	,086	,023	,469	,639	,213	4,701
	I_7	,071	,102	,024	,696	,486	,436	2,292
	I_8	-,043	,110	-,013	-,394	,694	,518	1,930
	I_9	,039	,086	,023	,457	,648	,210	4,771

a. Dependent Variable: LN_Paten

Figure 7: Coefficients table, LN_Paten dependent variable

These results support the role of LN_Fund as a robust mediator, while suggesting that LN_Paten plays a less consistent mediating role across models.

Mediation analysis per financial performance outcome

Revenue model

The first model that was analyzed is the revenue model. PROCESS model 4 was used to test if External funding (LN_Fund) and Number of patents (LN_Paten) mediate the effect of business type (b.type) on revenue growth (R.growth) while adjusting for industry (dummy variables, I_3–I_9) as the control variable (N = 139).

First, the model summary is analyzed. While explaining 19.5% of the variance in revenue growth the full mediation model is not statistically significant ($F(10, 128) = 1.61$, $p = .11$, $R^2 = .195$, moderate).

Model Summary

R	R-sq	MSE	F(HC3)	df1	df2	p
,4415	,1949	,0797	1,6135	10,0000	128,0000	,1097

Figure 8: Revenue model, Model summary

Next, the Total effect and the Direct effect are analyzed in order to see if there is a mediation effect existent. The Total effect ($b = -0.024$, $p = .69$) and the Direct effect ($b = 0.027$, $p = .67$) were statistically not significant, meaning Business type has no bivariate relationship with revenue growth and is not directly associated with revenue growth once the mediators are included. This means both hypothesis 1b and hypothesis 5b can be rejected since they expected a significantly better performance of USOs compared to deep-tech organizations in terms of revenue growth when not controlling for mediating variables and when controlling for mediating variables respectively.

Total effect of X on Y

Effect	se(HC3)	t	p	LLCI	ULCI
-,0238	,0599	-,3973	,6918	-,1423	,0947

Direct effect of X on Y

Effect	se(HC3)	t	p	LLCI	ULCI
,0266	,0631	,4223	,6735	-,0981	,1514

Figure 9: Revenue model, total and direct effect

While no initial mediation effect is found, the effect from the mediating variables on the dependent variable is evaluated in order to test for a potential indirect effect. A significant effect from a mediating variable on the dependent variable could be the first signs of an indirect effect. External funding showed to be significantly, positively related to revenue growth ($b = .131$, $p = .007$) meaning the revenue of firms that secure more on external funding grows faster. Patent had no measurable effect on revenue growth ($b = .042$, $p = .76$).

Model

	coeff	se(HC3)	t	p	LLCI	ULCI
constant	,1214	,1189	1,0216	,3089	-,1138	,3566
B.Type	,0266	,0631	,4223	,6735	-,0981	,1514
LN_Fund	,1309	,0476	2,7509	,0068	,0367	,2250
LN_Paten	,0417	,1385	,3008	,7640	-,2323	,3156

Figure 10: Revenue model, b path

Finally, the indirect effects are analyzed in order to test for relation between the independent and dependent variable via the mediating variable. In this case this means testing if organization type influences revenue growth via external funding and amount of patents granted. Business type exerted a significant indirect, negative influence on revenue growth via external funding (95% CI [-0.1079 - 0.0057]). This means hypothesis 3b can be accepted. While business type does not have a direct effect on revenue growth, the data indicates a significant indirect effect via external funding. USOs, by securing more external funding, experience higher revenue growth, confirming the hypothesized mediating phenomena. The indirect route through patents is not significant (95% CI [-0.0144 0.0246]), meaning hypothesis 4b can be rejected since this expected number of patents to mediate the effect of business type on revenue growth. All the industry dummies do not show significant effects, suggesting no hidden industry bias. Due to the direct effect being not significant, the data suggests a full mediation through external funding.

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	-,0504	,0277	-,1061	,0071
LN_Fund	-,0485	,0261	-,1079	-,0057
LN_Paten	-,0019	,0092	-,0144	,0246

Figure 11: Revenue model, indirect effects

In conclusion this means that after controlling for industry, business type does not predict revenue growth individually. Instead, it influences the total acquired external funding. Deep-tech organizations tend to secure less external funding compared to USOs. Because external funding is positively linked to revenue growth, this shortfall suppresses their growth prospects. Patent accumulation does not appear to transmit the effect of business type on growth.

Employee model

The second model that was analyzed is the employee model. PROCESS model 4 was used to test if External funding (LN_Fund) and Number of patents (LN_Paten) mediate the effect of business type (B.Type) on employee growth (E.Growth) while adjusting for industry (dummy variables I_2–I_9) as control variables (N = 573).

The full mediation model is statistically significant ($F(11, 561) = 10.47$, $p < .001$, $R^2 = .170$, moderate) and explains 17% of the variance in employee growth.

Model Summary

R	R-sq	MSE	F(HC3)	df1	df2	p
,4126	,1703	,0334	10,4660	11,0000	561,0000	,0000

Figure 12: Employee model, Model summary

The results showed a significant total effect of organization type on employee growth (b = -0.052, p = .003), indicating that Deep-tech organizations tend to exhibit a 5.2% lower employee growth compared to USOs (equivalently, USOs grow ~5.5% faster compared to Deep-tech organizations). This means hypothesis 1c can be accepted. When controlling for mediators, the direct effect remained significant (B = -0.038, p = .027). The reduction in absolute size from –0.052 to –0.038 (~26%) indicates that part of the effect is transmitted through one or more mediators, suggesting partial mediation. This means hypothesis 5c can be accepted since it expected the direct effect to remain significant after the inclusion of mediating variables.

Total effect of X on Y

Effect	se(HC3)	t	p	LLCI	ULCI
-,0516	,0171	-3,0101	,0027	-,0852	-,0179

Direct effect of X on Y

Effect	se(HC3)	t	p	LLCI	ULCI
-,0383	,0173	-2,2156	,0271	-,0723	-,0043

Figure 13: Employee model, total and direct effect

External funding is significantly related to employee growth (b = 0.053, p < .001), meaning the workforce of firms that secure more external funding grows faster. The number of patents has no measurable effect on employee growth (b = -.006, p = .77). Three industry dummy variables (I_5 (Health), I_6 (Industry & Engineering), and I_9 (Technology & Infrastructure)) were statistically significant predictors of employee growth, suggesting differences between specific industries.

Model

	coeff	se(HC3)	t	p	LLCI	ULCI
constant	,0005	,0399	,0123	,9902	-,0779	,0789
B.Type	-,0383	,0173	-2,2156	,0271	-,0723	-,0043
LN_Fund	,0532	,0107	4,9513	,0000	,0321	,0742
LN_Paten	-,0060	,0200	-,2979	,7659	-,0452	,0333
I_2	,0581	,0487	1,1915	,2340	-,0376	,1537
I_3	-,0067	,0579	-,1156	,9080	-,1204	,1070
I_4	-,0581	,0495	-1,1746	,2407	-,1553	,0391
I_5	,0595	,0434	1,3724	,1705	-,0257	,1447
I_6	,0776	,0466	1,6646	,0966	-,0140	,1693
I_7	-,0247	,0542	-,4557	,6488	-,1312	,0818
I_8	,0625	,0629	,9945	,3204	-,0610	,1861
I_9	,0739	,0458	1,6139	,1071	-,0160	,1639

Figure 14: Employee model, b path

Business type has a significant indirect, negative influence on employee growth via external funding (95 % CI [-0.0257 -0.0036]), indicating that organization type influences employee growth through its impact on funding. This means hypothesis 3c can be accepted since it expected external funding to significantly mediate the effect of business type on employee growth. The indirect route through patents is not significant (95 % CI [-0.0015 0.0020]), meaning hypothesis 4c can be rejected.

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	-,0133	,0057	-,0252	-,0034
LN_Fund	-,0134	,0057	-,0257	-,0036
LN_Paten	,0001	,0008	-,0015	,0020

Figure 15: Employee model, indirect effects

Roughly 26% of the total effect is explained by the mediators, but because the direct effect remains significant the data indicate partial mediation through external funding.

In conclusion, when controlling for industry, USOs grow faster compared to Deep-tech organizations in terms of employees. Part of this effect operates through differences in external funding. Deep-tech organizations tend to secure less external funding compared to USOs. Because external funding is positively linked to employee growth this suppresses their employee growth. Accounting for the number of patents does not influence the effect of business type on employee growth.

Survival model

The third model that was analyzed is the survival model. A baseline logistic-regression model was first estimated to establish the total effect of business type (B.Type) on survival (Status) while adjusting for industry dummies (dummy variables I_2–I_9) as control variables, but without the mediator variables. This model explained 11.4% of the variance in survival (Nagelkerke $R^2 = .114$, moderate) and showed that deep-tech start-ups are less likely remain active compared to USOs ($B = -1.374$, $p < .001$). Exponentiating the coefficient for business type (–1.374) gives an odds ratio of 0.253. This means that, while holding other variables constant, deep-tech organizations have about 75% lower odds of surviving compared to university spin-offs (USOs). This confirms hypothesis 1a which stated USOs are more likely to remain active compared to deep-tech organizations.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1118,341[a]	,055	,114

Figure 16: Survival model, model summary baseline regression

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	B.Type(1)	-1,374	,200	47,083	1	<,001	,253

Figure 17: Survival model, baseline regression

PROCESS model 4 for logistic regression was used to test whether External funding (LN_Fund) and Number of patents (LN_Paten) mediate the effect of business type (B.Type) on firm survival (Status) while adjusting for industry (dummy variables I_2–I_9) as control variables (N = 1 327).

The full mediation model explains 15.8 % of the variance in survival (Nagelkerke $R^2 = .158$, moderate) and is statistically significant (likelihood-ratio $\chi^2(11) = 103.81$, $p < .001$).

Model Summary

-2LL	ModelLL	df	p	McFadden	CoxSnell	Nagelkrk
751,4623	103,8131	11,0000	,0000	,1214	,0752	,1584

Figure 18: Survival model, model summary

The direct effect of business type on survival is significant in the log-odds metric (b = –1.46, $p < .001$), indicating that deep-tech organizations have significantly lower odds of surviving than USOs even after the two mediators are included. A change in business type multiplies the odds of survival by e^-1.46 ≈ 0.23, meaning 77% reduction in survival odds. The unadjusted descriptive table shows this means survival falls from 95.9% (USOs) to 84.8% (Deep-tech). Given that 95.9% of USOs survive, USOs are about 14% more likely to survive compared to Deep-tech firms after controlling for mediating variables. This means hypothesis 5a can be accepted since it expected USOs to outperform deep-tech organizations in terms of survival even after including mediation variables.

Direct effect of X on Y

Effect	se	Z	p	LLCI	ULCI
-1,4592	,2865	-5,0930	,0000	-2,0207	-,8976

Figure 19: Survival model, direct effect

		B.Type 0 Count	B.Type 1 Count
Status	0	35	154
	1	814	863

Figure 20: Survival model, descriptive table

External funding is positively related to survival (b = 0.56, p = .001), meaning firms that secure more external capital have higher odds of surviving. Exponentiating the coefficient gives an odds ratio of ≈ 1.74 per one-unit increase in LN_Fund. This means every time an organization realizes a ~2.7 times increase in its External funding + 1, its odds of surviving increase by about 74%. The corresponding difference in survival probability depends on the firm's starting point. Number of patents shows no significant effect on the probability of survival (b = .154, p = .52).

Model

	coeff	se	Z	p	LLCI	ULCI
constant	2,3758	,4437	5,3543	,0000	1,5061	3,2454
B.Type	-1,4592	,2865	-5,0930	,0000	-2,0207	-,8976
LN_Fund	,5555	,1701	3,2666	,0011	,2222	,8888
LN_Paten	,1541	,2384	,6464	,5180	-,3131	,6212

Figure 21: Survival model, b path

A statistically significant indirect, negative influence of business type via external funding is found (95 % CI [-0.454 -0.116]). The indirect route through patents is not significant (95 % CI [-0.085 0.017]). Due to the direct effect remaining significant, these results suggest a partial mediation through external funding. This means hypothesis 3a can be accepted since it expected a partial mediation effect from external funding on the relationship between business type and survival. Hypothesis 4a can be rejected since no significant mediation effect of number of patents was observed.

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	-,2589	,1198	-,4975	-,1158
LN_Fund	-,2477	,0885	-,4541	-,1160
LN_Paten	-,0112	,0701	-,0847	,0165

Figure 22: Survival model, indirect effect

In conclusion, after controlling for industry, USOs are more likely to survive compared to Deep-tech organizations. Part of this relationship is explained by differences in external funding. Deep-tech organizations secure less external funding compared to USOs. Due to external funding improving the probability of survival, this difference in external finance acquisition partially explains their lower survival rates. It does however not completely account for the lower survival rate since the direct effect of business type still remains significant after the inclusion of the mediating variables. Patent accumulation does not appear to transmit the effect of business type on survival.

IPO/M&A model

The final model that was analyzed is the IPO/M&A model. A baseline logistic-regression model was estimated to establish the total effect of business type (B.Type) on IPO or M&A achievement (IPO_M.A), while adjusting for industry dummies (I_2–I_9) as control variables and excluding the mediators. This model explained 4.7% of the variance in IPO/M&A achievement (Nagelkerke $R^2 = .047$, weak) and showed that deep-tech organizations are significantly more likely to achieve an IPO or M&A compared to USOs ($B = 0.638$, $p = .001$). Exponentiating the coefficient for business type yields an odds ratio of 1.89. This means that, while holding all other variables constant, deep-tech organizations have approximately 89% higher odds of reaching an IPO or M&A outcome than USOs. This rejects hypothesis 1d, which expected that USOs would significantly outperform deep-tech organizations in IPO/M&A achievement.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	973,834[a]	,019	,047

Figure 23: IPO/M&A achievement model, model summary baseline regression

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	B.Type(1)	,638	,198	10,389	1	,001	1,892

Figure 24: IPO/M&A achievement model, baseline regression

PROCESS model 4 for logistic regression was used to test whether External funding (LN_Fund) and Number of patents (LN_Paten) mediate the effect of business type (B.Type) on the likelihood that a firm achieves an IPO or M&A (IPO_M.A, 0 = not achieved, 1 = achieved), while adjusting for industry (dummy variables I_2–I_9) as control variables (N = 1 332).

The model is statistically significant overall (likelihood-ratio $\chi^2(11) = 71.43$, $p < .001$) and accounts for 15.9 % of the variation in IPO/M&A outcomes (Nagelkerke $R^2 = .159$, moderate).

```
Model Summary
      -2LL     ModelLL        df          p   McFadden    CoxSnell    Nagelkrk
  459,7662    71,4314    11,0000      ,0000      ,1345       ,0522       ,1588
```

Figure 25: IPO/M&A achievement model, model summary

The direct effect of business type on IPO/M&A achievement is significant in the log-odds metric (b = 0.91, p = .004), indicating that deep-tech organizations have significantly higher odds of achieving an IPO/M&A compared to USOs even after the two mediators and industry control variables are included. A change in business type multiplies the odds of achieving an IPO or M&A by e^0.91 ≈ 2.48, representing a 148% increase in IPO/M&A achievement odds. The unadjusted descriptive table shows IPO/M&A achievement rises from 4.9% for USOs to 9.9% for deep-tech firms, meaning USOs are have a roughly 50% lower probability than comparable Deep-tech organizations to reach an IPO or M&A. This means hypothesis 5d can be rejected since it expected USOs to outperform deep-tech organizations in terms of IPO/M&A achievement even after including mediation variables.

```
Direct effect of X on Y
     Effect         se          Z          p       LLCI       ULCI
      ,9084      ,3143     2,8901      ,0039      ,2924     1,5244
```

Figure 26: IPO/M&A achievement model, direct effect

		B.Type 0 Count	B.Type 1 Count
IPO_M.A	0	808	923
	1	42	101

Figure 27: IPO/M&A achievement model, descriptive table

External funding is positively related to IPO/M&A success ($b = 0.51$, $p < .001$). Exponentiating this coefficient results in an odds ratio of ≈1.66 per one-unit increase in LN_Fund, meaning that each time a firm realizes roughly a 2.7-fold increase in External funding + 1, its odds of achieving an IPO/M&A rise by about 66%. Number of patent is positively related to IPO/M&A success ($b = 0.40$, $p < .001$). Exponentiating this coefficient yields an odds ratio of ≈1.49 per one-unit increase in LN_Paten, meaning that every time a firm realizes roughly a 2.7-fold increase in its Patent count + 1, its odds of achieving an IPO or M&A rise by about 49%. For both funding and number of patents the exact change in IPO/M&A achievement probability depends on the firm's baseline.

Model

	coeff	se	Z	p	LLCI	ULCI
constant	-3,6682	,7522	-4,8765	,0000	-5,1425	-2,1939
B.Type	,9084	,3143	2,8901	,0039	,2924	1,5244
LN_Fund	,5056	,0964	5,2436	,0000	,3166	,6946
LN_Paten	,3961	,1094	3,6199	,0003	,1816	,6106

Figure 28: IPO/M&A achievement model, b path

A significant negative, indirect effect of business type operates through external funding (95 % CI [-0.350, -0.136]). Because deep-tech firms raise less external capital compared to USOs, the lower acquired external funding reduces part of their otherwise higher probability to achieve an IPO/M&A. The indirect path through patents is not significant (95 % CI [-0.066, 0.005]). The total indirect effect remains negative and significant (95 % CI [-0.390, -0.151]). Because the direct effect of business type stays significant after the mediators are included, the results suggest a partial, suppression mediation via external funding. This means hypothesis 3d can be rejected. The indirect path via funding is significant and negative, but it works differently than expected. It suppresses the deep-tech IPO/M&A advantage rather than producing a USO advantage. Also hypothesis 4d can be rejected since no significant mediation effect is observed from number of patents.

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	-,2545	,0588	-,3902	-,1509
LN_Fund	-,2256	,0546	-,3503	-,1357
LN_Paten	-,0289	,0183	-,0658	,0053

Figure 29: IPO/M&A achievement model, indirect effects

In summary, after controlling for industry, Deep-tech organizations are more likely to reach an IPO or M&A compared to USOs, yet their comparatively lower levels of external funding reduce that likelihood. While number of patents is independently related to IPO/M&A achievement, it does not significantly mediate the effect of business type once external funding differences are also taken into account.

The complete results of all SPSS models can be found in appendix E.

Discussion

The analysis of the four mediation models across the performance measurements (survival, revenue growth, employee growth and IPO/M&A achievement) yielded mixed results, partially aligning with and partially diverging from expectations.

While USOs are characterized by large founding management teams which are evaluated as an important indicator of start-up performance across all performance metrics in previous research, this research finds no significant difference between the founding team sizes of USOs and Deep-tech organizations. Additionally, no significant indirect effect between organization type and performance metric via team size were found.

Founding management team size was operationalized as the number of individuals formally listed as founders at the moment of incorporation and was intended as a proxy for the team's commercial and operational expertise, as well as its social diversity. However, this measurement is incapable of measuring these qualitative dimensions, which are arguably more influential for firm performance than the number of founders alone. By operationalizing the construct to a quantitative measure, this research limits its internal validity and excluded potentially important qualitative attributes. This choice may explain why the models found no significant relationship between team size and financial performance.

The findings suggest that USOs are more likely to survive and achieve higher levels of employee growth compared to Deep-tech organizations. This effect remains after accounting for mediating variables which indicates USOs benefit in terms of financial performance as result of their unique characteristics, being their university relationship. However, the findings of this research suggest that USOs are significantly less likely to reach an IPO or M&A compared to Deep-tech organizations, even after controlling for the higher levels of external funding acquired by USOs. The effect suggests that capital availability is not the binding constraint, but rather structural and strategic factors inherent to USOs appear to impede the translation of research-based innovations into IPO/M&A achievement. In particular, qualitative founding team factors emerge as a plausible mechanism. USO founding teams are frequently led by academic teams who possess deep scientific expertise but more limited managerial experience and commercial knowledge (Munari et al., 2015). Such teams often prioritize technological advancement and knowledge dissemination over aggressive market penetration, resulting in weaker sales orientation and less rigorous go-to-market execution. This ultimately reduces exit potential of the venture. By contrast, Deep-tech organizations typically assemble commercially experienced founding teams and pursue exit-oriented growth strategies from inception, positioning them more favourably for IPO or M&As. These findings show the importance of entrepreneurial capabilities and market-focused strategies when converting scientific breakthroughs into successful financial exits.

The results of this research show that access to external funding is the only consistently robust mechanism through which USOs achieve superior performance. After controlling for industry, USOs raise significantly more capital, which partially mediates the relationship between business type and financial performance. In the early-development phases, external funding help the organization to deal with the liabilities of newness, potentially by financing product development, market validation and key technical human resources, ultimately enhancing survival odds. These activities would be challenging using internal finance alone. As firms transition to the growth stage, external funding supports the scaling operations, thereby accelerating employee growth. During the exit stages of the organization, external funding signals quality and reduces information asymmetries, partially offsetting the advantage that deep-tech organisations exhibit in exit markets. Beyond pure cash advantages, external funding supplies social capital in terms of management expertise, strategic partnerships and legitimacy. Taken together, these advantages explain the indirect effect of business type on financial performance via external funding, and show how external funding is critical for surviving, growing, and achieving a successful financial exit.

By contrast, the number of patents held by a startup offered no explanatory power across most performance metrics, with the single exception being IPO/M&A achievement. The lack of consistent significance suggests that proprietary knowledge alone is insufficient to drive performance without access to complementary assets, most notably financial resources. This finding aligns with Teece's (1986) framework which suggests that successful commercialization of innovation not only depends on intellectual-property ownership but also on the control of complementary assets such as financing, managerial expertise, manufacturing, and market-access capabilities. In this context, simply counting patents may obscure more meaningful dimensions of intellectual property, such as their technological quality or economic value.

Limitations and recommendations

Although this research provides valuable insights in the financial performance of USOs compared to non-USO Deep-tech organizations, there are constraints which temper the generalisability of the findings. Some of these limitations suggest direction for future research to improve the knowledge in this field.

Data completeness constitutes the most important limitation of this research. Acquiring a complete database proved to be more challenging than initially expected, which potentially limits the external validity of this research. Approximately 90 percent of revenue-growth observations were missing and were removed in the analysis via list-wise deletion. Because the disclosure of financial results to a commercial database is not obligated, these exclusions potentially bias the sample toward larger or faster-growing organizations and thus bias performance estimates. Ultimately, the low levels of observation for certain measurements reduce the external validity of the results.

In an ideal design, researchers would assemble a database based on mandatory filings (e.g. annual accounts and tax returns). These legally required documents include firms across the entire growth spectrum, thereby minimizing selection bias. Securing formal data-sharing agreements with the authorities storing this data would provide a database with near perfect completion. Enhancing these administrative records with information from commercial databases would further enrich the dataset, resulting in an exceptionally robust empirical foundation. These measures would improve data completeness and external validity, enabling more reliable analysis of startup performance.

Secondly, translating abstract theoretical constructs into quantitative metrics has proven to be challenging and involved compromise. Innovativeness, a multidimensional concept, was proxied by the number of granted patents. While the number of patents offers a measurable indicator of inventive activity, it purely focusses on quantity and ignores technological significance. Consequently, the variable captures only a part of the underlying concept, reducing construct validity.

To achieve a more complete operationalisation, future research should adopt composite measures. Possible components for this measurement include R&D expenditure, which reflects the input intensity of the innovation, and patent indices, which approximate technological impact. While each measurement has individual limitations, integrating them in an composite variable framework would provide a richer measure of the level of innovativeness.

Finally, this research treats USOs as a homogeneous class and therefore overlooks intra-group heterogeneity. However, heterogeneity within the USO group is expected and could lead to interesting research. A critical source of variation is the arrangement that binds a spin-off to its parent university.

These relationships are typically formalized through licensing agreements, equity agreements, or through a combination of both. Each agreement offers different implications for the university-USO relationship and subsequently financial performance. Analysing these subtypes may reveal performance patterns such as superior scaling in equity-backed spin-offs or faster commercialisation in licence-only firms. While not completely fitting to the scope of this research these factors were not considered. However, future researchers should examine differences within USOs in order to achieve even greater understanding of their financial performance.

Although research in the field of university linkages and financial performance outcomes is rising (Bolzani et al., 2021; Hellmann et al., 2023 e.g.), formalizing university linkages remains a topic of debate. Future studies should therefore model governance type as a moderating variable in the models utilized in this research, assessing whether equity, licensing, or hybrid contracts affect survival, growth and IPO/M&A achievement. Such evidence would provide valuable insights and actionable guidance for universities and founders on structuring spin-off agreements that maximise long-term financial performance.

Practical implications

This research offers multiple practical implications for stakeholders engaged in the development and support of USOs, including TTOs, investors, university administrators, and policy makers.

Firstly, the results of this research show the higher survival probabilities and faster employment growth of USOs compared to deep-tech organizations. This performance profile presents a relative lower risk (higher chance of survival) and higher-growth (faster employment growth) scenario, which is an attractive risk-profile for investors. Additionally, USO management teams and TTOs can leverage this evidence to better position USOs when acquiring external funding. It presents USOs as a robust investment opportunities for growth and stability.

Secondly, the results of this research underline the crucial role that access to external funding plays in the financial success of USOs, potentially by providing essential resources for R&D and signalling credibility and growth potential to investors and partners. This has practical implications for the management team of USOs. Using this knowledge they should prioritise acquiring external funding in order to boost their growth and enhance their chances of survival and IPO/M&A achievement.

Collectively, these insights enable USO management teams to make more informed strategic decisions and give TTOs the evidence needed to refine their support mechanisms. Furthermore, policy makers can draw from these findings to allocate funding and support to impactful initiatives. Finally, by recognizing USOs as robust and scalable investment opportunities, investors can refine their funding allocation.

Conclusion

The aim of this research was to achieve an improved understanding of the financial performance of USOs in order to foster their development and increase their social and economic impact. This was done by comparing USOs to deep-tech organizations. Additionally, this research aimed to analyze whether this effect is partially mediated by founding management team, external funding and innovativeness. In order to address this gap in the known literature, this research asked the question:

> *Which characteristics of USOs influence their financial performance compared to Deep-tech organizations in the Dutch startup ecosystem?*

Drawing on four seperate models, the evidence supports a partial-mediation narrative. USOs outperform deep-tech firms in survival probability (14% more likely to survive) and employee growth (5.5% faster growth), yet lag behind them in IPO/M&A achievement (50% less IPO/M&As). The influence of business type on financial perfomance is partially transmitted trough different access to external funding. After controling for industry, USOs aqcuire significantly higher levels of external funding (roughly 56% more). This partially explains the higher performance in terms of survival and employee growth, yet doesn't completely supresses the higher perfromance Deep-tech organizations experience in terms of IPO/M&A achievement. Other potential mediating variables, being number of patents and founding management team size, did not show consistent significant results. It is for this reason this reasearch only finds external funding as an explanation for the superior performance of USOs in terms of survival and employee growth. However, a residual direct effect of business type on performance persists after controlling for the mediating variables. This plausibly reflects advantages associated with the university relationship that are not completely explained by the mediation variables, such as access to networks, legal assistance and HR services.

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Appendices

Appendix A: Recoded industries

Old primary industy classification	New industry classification	Code
No industry classification	No industry classification	0
Enterprise software Hosting Security Semiconductors Telecom	Technology & Infrastructure	9
Fashion Food Home living Wellness beauty Kids Dating	Consumer Products & Lifestyle	2
Gaming Media Music Event tech Sports	Media & Entertainment	7
Fintech Legal Jobs recruitment Marketing Real estate	Finance & Business Services	4
Education Edtech	Education & Knowledge	3
Health	Health	5
Engineering and manufacturing equipment Robotics Energy Space Chemicals	Industry & Engineering	6
Transportation Travel	Mobility & Travel	8

Appendix B: Initial descriptive statistics

Statistics

		B.Type	R.Growth	E.Growth	Status	IPO_M.A	TeamSize	FundingM	Patents
N	Valid	1874	189	781	1866	1874	1165	1332	1874
	Missing	0	1685	1093	8	0	709	542	0
Mean		,55	,16192	,06001	,90	,08	1,88	4,76529	17,63
Skewness		-,187	1,964	,576	-2,645	3,194	1,958	7,755	35,481
Std. Error of Skewness		,057	,177	,087	,057	,057	,072	,067	,057
Kurtosis		-1,967	10,350	1,635	5,002	8,213	6,499	72,054	1345,405
Std. Error of Kurtosis		,113	,352	,175	,113	,113	,143	,134	,113

Appendix C: Indirect effects management team size

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	-,0343	,0315	-,0945	,0348
TeamSize	-,0002	,0060	-,0153	,0103
LN_Fund	-,0323	,0279	-,0947	,0182
LN_Paten	-,0018	,0120	-,0166	,0330

Figure C1: Indirect effect from mediating variables on revenue growth, teamsize not significant

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	-,0068	,0059	-,0191	,0040
TeamSize	,0007	,0015	-,0021	,0044
LN_Fund	-,0076	,0059	-,0200	,0033
LN_Paten	,0002	,0010	-,0016	,0026

Figure C2: Indirect effect from mediating variables on employee growth, teamsize not significant

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	-,1522	,1484	-,3709	-,0494
TeamSize	-,0168	,0247	-,0772	,0194
LN_Fund	-,1366	,0821	-,3420	-,0361
LN_Paten	,0011	,1230	-,0239	,0382

Figure C3: Indirect effect from mediating variables on survival, teamsize not significant

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	-,1004	,0565	-,2206	-,0005
TeamSize	,0143	,0270	-,0335	,0751
LN_Fund	-,1056	,0490	-,2156	-,0269
LN_Paten	-,0091	,0213	-,0512	,0351

Figure C4: Indirect effect from mediating variables on IPO/M&A achievement, teamsize not significant

Appendix D: Four mediation models

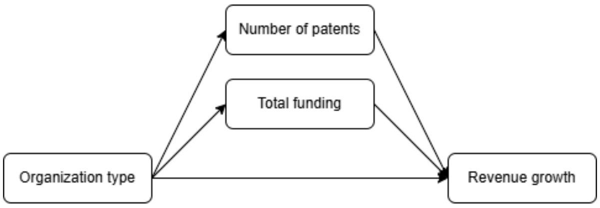

Figure D1: Revenue Model

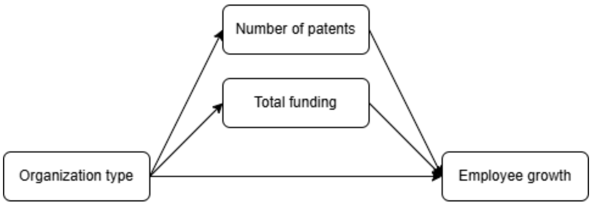

Figure D2: Employee Model

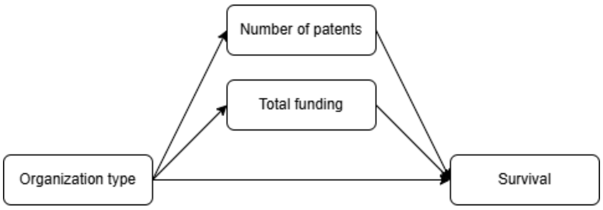

Figure D3: Survival Model

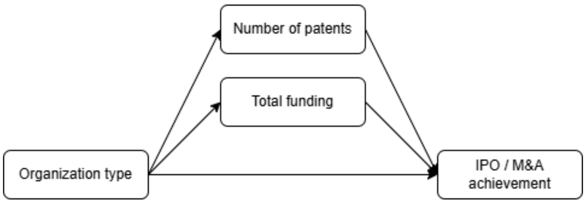

Figure D4: IPO/M&A achievement Model

Appendix E: SPSS Output per model

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.0 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : R.Growth
    X  : B.Type
   M1  : LN_Fund
   M2  : LN_Paten

Covariates:
 I_3      I_4      I_5      I_6      I_7      I_8      I_9

Sample
Size:  139
```

Figure E1: Revenue model output (PROCESS) – Part 1

```
**************************************************************************
OUTCOME VARIABLE:
 R.Growth

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,4415      ,1949      ,0797     1,6135    10,0000   128,0000      ,1097

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant      ,1214      ,1189     1,0216      ,3089     -,1138      ,3566
B.Type        ,0266      ,0631      ,4223      ,6735     -,0981      ,1514
LN_Fund       ,1309      ,0476     2,7509      ,0068      ,0367      ,2250
LN_Paten      ,0417      ,1385      ,3008      ,7640     -,2323      ,3156
I_3          -,0565      ,1420     -,3977      ,6915     -,3375      ,2246
I_4          -,0721      ,1602     -,4502      ,6533     -,3892      ,2449
I_5          -,0772      ,1504     -,5132      ,6087     -,3748      ,2204
I_6          -,1000      ,1461     -,6843      ,4950     -,3891      ,1891
I_7          -,0480      ,2118     -,2265      ,8212     -,4670      ,3710
I_8          -,0526      ,1831     -,2871      ,7745     -,4148      ,3097
I_9          -,0497      ,1541     -,3225      ,7476     -,3546      ,2552
```

Figure E2: Revenue model output (PROCESS) – Part 2

```
************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 R.Growth

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,1598      ,0255      ,0950      ,6899     8,0000   130,0000      ,6999

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant      ,2649      ,1491     1,7769      ,0779     -,0300      ,5599
B.Type       -,0238      ,0599     -,3973      ,6918     -,1423      ,0947
I_3          -,1450      ,1783     -,8133      ,4176     -,4977      ,2077
I_4          -,1323      ,1882     -,7026      ,4836     -,5047      ,2402
I_5          -,0885      ,1678     -,5272      ,5989     -,4205      ,2436
I_6          -,1774      ,1794     -,9885      ,3248     -,5323      ,1776
I_7          -,0787      ,2139     -,3681      ,7134     -,5020      ,3445
I_8          -,0927      ,2004     -,4626      ,6444     -,4891      ,3037
I_9          -,0550      ,1738     -,3165      ,7522     -,3989      ,2889
```

Figure E3: Revenue model output (PROCESS) – Part 3

```
************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect    se(HC3)          t          p       LLCI       ULCI
     -,0238      ,0599     -,3973      ,6918     -,1423      ,0947

Direct effect of X on Y
     Effect    se(HC3)          t          p       LLCI       ULCI
      ,0266      ,0631      ,4223      ,6735     -,0981      ,1514

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
TOTAL        -,0504      ,0277     -,1061      ,0071
LN_Fund      -,0485      ,0261     -,1079     -,0057
LN_Paten     -,0019      ,0092     -,0144      ,0246

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

NOTE: A heteroscedasticity consistent standard error and covariance matrix estimator was used.

NOTE: Due to estimation problems, some bootstrap samples had to be replaced.
      The number of times this happened was:
      274

------ END MATRIX -----
```

Figure E4: Revenue model output (PROCESS) – Part 4

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.0 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : E.Growth
    X  : B.Type
   M1  : LN_Fund
   M2  : LN_Paten

Covariates:
 I_2      I_3      I_4      I_5      I_6      I_7      I_8      I_9

Sample
Size:  573
```

Figure E5: Employee model output (PROCESS) – Part 1

```
**************************************************************************
OUTCOME VARIABLE:
 E.Growth

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,4126      ,1703      ,0334    10,4660    11,0000   561,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant      ,0005      ,0399      ,0123      ,9902     -,0779      ,0789
B.Type      -,0383      ,0173    -2,2156      ,0271     -,0723     -,0043
LN_Fund       ,0532      ,0107     4,9513      ,0000      ,0321      ,0742
LN_Paten     -,0060      ,0200     -,2979      ,7659     -,0452      ,0333
I_2           ,0581      ,0487     1,1915      ,2340     -,0376      ,1537
I_3          -,0067      ,0579     -,1156      ,9080     -,1204      ,1070
I_4          -,0581      ,0495    -1,1746      ,2407     -,1553      ,0391
I_5           ,0595      ,0434     1,3724      ,1705     -,0257      ,1447
I_6           ,0776      ,0466     1,6646      ,0966     -,0140      ,1693
I_7          -,0247      ,0542     -,4557      ,6488     -,1312      ,0818
I_8           ,0625      ,0629      ,9945      ,3204     -,0610      ,1861
I_9           ,0739      ,0458     1,6139      ,1071     -,0160      ,1639
```

Figure E6: Employee model output (PROCESS) – Part 2

```
************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 E.Growth

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,3017      ,0910      ,0364     7,5972     9,0000   563,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant      ,0046      ,0406      ,1123      ,9106     -,0752      ,0844
B.Type       -,0516      ,0171    -3,0101      ,0027     -,0852     -,0179
I_2           ,1076      ,0483     2,2278      ,0263      ,0127      ,2024
I_3           ,0010      ,0600      ,0171      ,9864     -,1168      ,1189
I_4          -,0344      ,0500     -,6883      ,4915     -,1325      ,0637
I_5           ,1087      ,0427     2,5446      ,0112      ,0248      ,1926
I_6           ,1299      ,0472     2,7532      ,0061      ,0372      ,2227
I_7          -,0024      ,0542     -,0449      ,9642     -,1090      ,1041
I_8           ,0968      ,0616     1,5703      ,1169     -,0243      ,2179
I_9           ,1255      ,0462     2,7167      ,0068      ,0348      ,2162
```

Figure E7: Employee model output (PROCESS) – Part 3

```
************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect    se(HC3)          t          p       LLCI       ULCI
     -,0516      ,0171    -3,0101      ,0027     -,0852     -,0179

Direct effect of X on Y
     Effect    se(HC3)          t          p       LLCI       ULCI
     -,0383      ,0173    -2,2156      ,0271     -,0723     -,0043

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
TOTAL        -,0133      ,0057     -,0252     -,0034
LN_Fund      -,0134      ,0057     -,0257     -,0036
LN_Paten      ,0001      ,0008     -,0015      ,0020

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

NOTE: A heteroscedasticity consistent standard error and covariance matrix estimator was used.

------ END MATRIX -----
```

Figure E8: Employee model output (PROCESS) – Part 4

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1118,341[a]	,055	,114

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001.

Figure E9: Survival (baseline logistic regression)– Part 1

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	B.Type(1)	-1,374	,200	47,083	1	<,001	,253
	I_2(1)	,877	,464	3,565	1	,059	2,404
	I_3(1)	,243	,603	,162	1	,687	1,275
	I_4(1)	-,171	,399	,184	1	,668	,843
	I_5(1)	1,144	,404	8,002	1	,005	3,140
	I_6(1)	,722	,396	3,321	1	,068	2,059
	I_7(1)	,322	,450	,512	1	,474	1,380
	I_8(1)	,068	,472	,020	1	,886	1,070
	I_9(1)	1,071	,406	6,946	1	,008	2,917
	Constant	2,461	,370	44,312	1	<,001	11,715

a. Variable(s) entered on step 1: B.Type, I_2, I_3, I_4, I_5, I_6, I_7, I_8, I_9.

Figure E10: Survival (baseline logistic regression)– Part 2

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.0 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Status
    X  : B.Type
   M1  : LN_Fund
   M2  : LN_Paten

Covariates:
 I_2      I_3      I_4      I_5      I_6      I_7      I_8      I_9

Sample
Size:  1327
```

Figure E11: Survival model output (PROCESS) – Part 1

```
**************************************************************************
OUTCOME VARIABLE:
 Status

Coding of binary Y for logistic regression analysis:
    Status  Analysis
       ,00       ,00
      1,00      1,00

Model Summary
       -2LL    ModelLL         df          p   McFadden   CoxSnell   Nagelkrk
   751,4623   103,8131    11,0000      ,0000      ,1214      ,0752      ,1584

Model
              coeff         se          Z          p       LLCI       ULCI
constant     2,3758      ,4437     5,3543      ,0000     1,5061     3,2454
B.Type      -1,4592      ,2865    -5,0930      ,0000    -2,0207     -,8976
LN_Fund       ,5555      ,1701     3,2666      ,0011      ,2222      ,8888
LN_Paten      ,1541      ,2384      ,6464      ,5180     -,3131      ,6212
I_2          1,1504      ,5686     2,0235      ,0430      ,0361     2,2648
I_3           ,2384      ,6928      ,3441      ,7308    -1,1195     1,5962
I_4          -,0995      ,4627     -,2150      ,8298    -1,0064      ,8075
I_5          1,0170      ,4735     2,1477      ,0317      ,0889     1,9450
I_6           ,9527      ,4751     2,0052      ,0449      ,0215     1,8839
I_7           ,2648      ,5158      ,5134      ,6077     -,7461     1,2757
I_8           ,2278      ,5690      ,4003      ,6890     -,8875     1,3430
I_9           ,9613      ,4707     2,0425      ,0411      ,0388     1,8839

These results are expressed in a log-odds metric.
```

Figure E12: Survival model output (PROCESS) – Part 2

```
****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          Z          p       LLCI       ULCI
    -1,4592      ,2865    -5,0930      ,0000    -2,0207     -,8976

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
TOTAL        -,2589      ,1198     -,4975     -,1158
LN_Fund      -,2477      ,0885     -,4541     -,1160
LN_Paten     -,0112      ,0701     -,0847      ,0165

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  1000

NOTE: A heteroscedasticity consistent standard error and covariance matrix estimator was used.

NOTE: Total effect model not available with dichotomous Y

NOTE: Direct and indirect effects of X on Y are on a log-odds metric.

------ END MATRIX -----
```

Figure E13: Survival model output (PROCESS) – Part 3

		B.Type	
		0	1
		Count	Count
Status	0	35	154
	1	814	863

Figure 14: Survival descriptives table

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	973,834[a]	,019	,047

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001.

Figure E15: IPO/M&A achievement (baseline logistic regression)– Part 1

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	B.Type(1)	,638	,198	10,389	1	,001	1,892
	I_2(1)	-1,512	,645	5,502	1	,019	,220
	I_3(1)	-1,440	1,090	1,746	1	,186	,237
	I_4(1)	-,480	,495	,939	1	,333	,619
	I_5(1)	-,439	,439	1,003	1	,317	,644
	I_6(1)	-,443	,451	,964	1	,326	,642
	I_7(1)	-,430	,547	,620	1	,431	,650
	I_8(1)	-,520	,614	,718	1	,397	,595
	I_9(1)	,168	,433	,150	1	,698	1,183
	Constant	-2,542	,410	38,444	1	<,001	,079

a. Variable(s) entered on step 1: B.Type, I_2, I_3, I_4, I_5, I_6, I_7, I_8, I_9.

Figure E16: IPO/M&A achievement (baseline logistic regression)– Part 2

IPO/M&A achievement model

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.0 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : IPO_M.A
    X  : B.Type
   M1  : LN_Fund
   M2  : LN_Paten

Covariates:
 I_2      I_3      I_4      I_5      I_6      I_7      I_8      I_9

Sample
Size:  1332
```

Figure E17: IPO/M&A achievement model output (PROCESS) – Part 1

****
OUTCOME VARIABLE:
IPO_M.A

Coding of binary Y for logistic regression analysis:

IPO_M.A	Analysis
,00	,00
1,00	1,00

Model Summary

-2LL	ModelLL	df	p	McFadden	CoxSnell	Nagelkrk
459,7662	71,4314	11,0000	,0000	,1345	,0522	,1588

Model

	coeff	se	Z	p	LLCI	ULCI
constant	-3,6682	,7522	-4,8765	,0000	-5,1425	-2,1939
B.Type	,9084	,3143	2,8901	,0039	,2924	1,5244
LN_Fund	,5056	,0964	5,2436	,0000	,3166	,6946
LN_Paten	,3961	,1094	3,6199	,0003	,1816	,6106
I_2	-2,2950	1,2485	-1,8382	,0660	-4,7420	,1520
I_3	-13,1517	666,8833	-,0197	,9843	-1320,2190	1293,9156
I_4	-,3382	,8336	-,4058	,6849	-1,9720	1,2955
I_5	-,7735	,7921	-,9765	,3288	-2,3260	,7790
I_6	-,6879	,8022	-,8576	,3911	-2,2601	,8843
I_7	-,7870	,9775	-,8051	,4208	-2,7028	1,1288
I_8	-,8687	1,0613	-,8186	,4130	-2,9488	1,2113
I_9	,1298	,7693	,1688	,8660	-1,3779	1,6375

These results are expressed in a log-odds metric.

Figure E18: IPO/M&A achievement model output (PROCESS) – Part 2

```
****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          Z          p       LLCI       ULCI
      ,9084      ,3143     2,8901      ,0039      ,2924     1,5244

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
TOTAL        -,2545      ,0588     -,3902     -,1509
LN_Fund      -,2256      ,0546     -,3503     -,1357
LN_Paten     -,0289      ,0183     -,0658      ,0053

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  1000

NOTE: A heteroscedasticity consistent standard error and covariance matrix estimator was used.

NOTE: Total effect model not available with dichotomous Y

NOTE: Direct and indirect effects of X on Y are on a log-odds metric.

------ END MATRIX -----
```

Figure E19: IPO/M&A achievement model output (PROCESS) – Part 3

		B.Type	
		0	1
		Count	Count
IPO_M.A	0	808	923
	1	42	101

Figure 20: IPO/M&A achievement descriptives table