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Does hiring a professional CEO at the founding stage improve startup outcomes compared to founder-led startups?

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Abstract

This thesis examines how founder-led and professional-led startups differ in performance using a dataset of 7,143 venture-backed firms in North America and Europe with manually validated CEO classifications. Professional-led startups raise more capital and fail less often, while founder-led startups show no exit disadvantage but face nearly twice the odds of failure. Yet founders who reach an IPO command valuations approximately twice as large as their professional-led counterparts. In the field of Artificial Intelligence, founder-led firms raise more funding. These patterns suggest that neither leadership type dominates universally. The optimal configuration depends on stage, sector, and context.

Keywords: Professional CEO, Founder-led startups, Entrepreneurial performance, Venture funding

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1. Introduction

When Andreessen Horowitz cofounder Ben Horowitz first raised venture capital (VC) for his startup Loudcloud, one of the firm's senior partners publicly asked him, "When are you going to get a real CEO?" Horowitz later described how this comment "knocked the wind out of me" and inspired him to build a deliberately "founder-friendly" venture capital firm (Eisenmann and Kind 2014). The episode captures a fundamental tension in startup governance: sophisticated investors openly disagree on whether technical founders should remain as CEOs (Chief Executive Officer) or be replaced by professional managers as their companies scale.

This disagreement plays out frequently. Approximately half of venture-backed founders are replaced as CEO within three years of initial funding (Wasserman 2003), yet the performance implications of these leadership structures remain poorly understood. The question matters because venture-backed startups, while representing less than 0.2% of new businesses, account for roughly 40% of newly public companies and drive disproportionate innovation and employment growth (Ritter 2014).

Existing research offers conflicting guidance. Some work emphasises founders' unique assets, deep technical expertise, product vision, and intrinsic commitment, while other studies highlight professional CEOs' strengths in organisational design, financial discipline, and scaling operations (Wasserman 2009; Hellmann and Puri 2002; Hsu 2007). The most rigorous evidence comes from Ewens and Marx (2018), who use variation in non-compete enforceability across U.S. states to show that investor-driven founder replacement can improve exit outcomes. However, their analysis focuses on one mechanism (replacement events), one country (the United States), and a narrow set of exit-related outcomes.

This thesis complements that causal evidence by providing a broader descriptive mapping of how founder-led and professionally led startups differ across multiple performance

dimensions. Using a dataset of 7,143 venture-backed firms with manually validated CEO information, the study examines funding outcomes, exit probabilities, failure risks, and valuations. Rather than attempting to isolate causal effects, the analysis documents where performance patterns diverge by CEO type and how these associations vary across industries and countries, offering an empirical benchmark that informs ongoing debates among investors and entrepreneurs about optimal leadership configurations.

2. Literature Review

2.1 Venture Capital, Governance, and Leadership

Venture capitalists do more than provide capital. They actively monitor portfolio firms, participate in strategic decisions, and frequently intervene in leadership structures. Gompers et al. (2019) document that 95 per cent of VCs describe the management team as a key investment factor. Nearly half name it the most important one. Historical evidence tells a similar story: investors often attribute portfolio failures to management weaknesses rather than technology or market problems (Gorman and Sahlman 1989).

This emphasis on human capital gives VCs strong incentives to shape leadership. Board seats, contractual covenants, and staged financing provide leverage to change management when investors see a mismatch between current capabilities and firm needs (Kaplan and Strömberg 2003). Chemmanur, Krishnan, and Nandy (2008) find that VC financing is associated with improved efficiency and survival. They attribute part of this to non-financial value that investors provide, including governance interventions. The founder–VC relationship thus becomes a central arena where leadership decisions are negotiated. The choice between founder and professional CEO is a recurring and consequential governance question.

2.2 Theoretical Perspectives on Founder and Professional CEOs

The literature offers competing views on whether founders or professional CEOs are better suited to lead startups. Work on founder-specific human capital emphasises that founders

possess deep knowledge of their product, technology, and early customers. They also tend to show strong emotional commitment to the venture (Wasserman 2009). Their personal networks and tacit knowledge are closely tied to the firm. This can provide advantages in early-stage innovation and opportunity recognition.

Research on startup professionalisation highlights different strengths. Hellmann and Puri (2002) show that VC involvement is associated with more formal processes and structured HR systems. Professional CEOs typically bring prior experience managing larger organisations and building commercial capabilities. They are often more skilled at interacting with investors and boards. These attributes become increasingly important as firms scale (Kaplan, Sensoy, and Strömberg 2009).

Signalling theory offers a third lens. Hsu (2007) argues that leaders' backgrounds signal to external stakeholders about firm quality. A technical founder may credibly signal opportunity quality in specialised domains. A professional CEO with scaling experience may instead signal readiness for growth and exit. Which signals investors value likely depends on the firm's stage and strategic context.

2.3 Founder–CEO Succession and Startup Performance

Empirical research has devoted considerable attention to founder-CEO succession. Wasserman (2001) documents that founder replacement is common, especially as firms raise funding and face new organisational challenges. He frames this as a trade-off between control and value. Founders who retain authority may constrain growth. Those who accept professionalisation may increase firm value at the cost of personal control.

Subsequent studies examine how leadership transitions relate to performance. Findings are mixed. Chen and Thompson (2015) use Danish register data and find that professionalisation is associated with a higher probability of quality exits. However, it also correlates with greater short-term failure risk. Leadership transitions can destabilise firms even when survivors

eventually perform well. Bernstein, Giroud, and Townsend (2016) document that intensive VC monitoring is associated with better exit outcomes for U.S. firms. They do not isolate specific mechanisms.

Ewens and Marx (2018) analyse founder replacement in over 22,000 U.S. VC-backed startups founded between 1995 and 2008. Naïve regressions show a negative correlation between founder replacement and successful exits. This is consistent with VCs replacing founders in troubled firms. To address this endogeneity, they exploit staggered changes in non-compete enforceability across 14 U.S. states. These changes serve as an instrument for the local supply of external executives. Instrumented regressions reverse the sign. Founder replacement increases the likelihood of high-quality exits, particularly when C-level founders are replaced and leave the firm. This provides causal evidence that investor-driven replacement can improve outcomes.

Other research cautions that replacing founders introduces challenges. Professional CEOs may hold smaller equity stakes and weaker ties to the organisation, potentially misaligning their incentives with those of investors (Wasserman 2003). New leaders also face learning curves in understanding the firm's technology, culture, and stakeholder relationships, which increases transition costs. Nelson (2003) notes that founder influence may persist even after formal succession. Such influence can shape organisational identity and create resistance to change.

2.4 Contextual Contingencies: Industry and Ecosystem

Recent work emphasises that leadership effectiveness depends on context. Industry characteristics influence both the capabilities leaders need and how investors evaluate them. Pisano (2006) shows that science-based industries, such as biotechnology, demand deep technical knowledge and long development cycles. This increases the value of domain-specific expertise. Similarly, in technically complex fields like Artificial Intelligence (AI),

founder credibility and scientific reputation may be central to securing resources. Founder-led firms could be particularly well-positioned in such sectors.

Country-level ecosystem differences also shape leadership dynamics. Kenney and Zysman (2016) describe how innovation-intensive economies depend on dense networks of investors, acquirers, and complementary firms. Ecosystem maturity affects financing availability, exit opportunities, and norms around founder control. U.S. markets are often characterised as founder-tolerant. Investors there may be more willing to back strong founder personalities. Other environments may emphasise earlier professionalisation and formal governance.

These contextual factors have an important implication. Performance differences between founder- and professional-led firms may vary across industries and geographies. Leadership configurations that work well in one setting may prove less effective in another.

2.5 Summary and Research Gap

Given these diverse perspectives, the literature reveals a paradox. Founder-CEO succession is both common and consequential in venture-backed startups. Yet empirical evidence on its performance implications remains surprisingly thin. Theoretical perspectives highlight distinct strengths of each leadership type. Founders bring vision, technical depth, and commitment. Professional CEOs bring operational discipline, investor credibility, and scaling experience. But theory does not resolve when each type creates more value. Empirical studies document that succession occurs frequently, often at investor instigation. They have not systematically compared outcomes across the full range of metrics that matter to founders and investors.

Within this limited empirical landscape, Ewens and Marx (2018) provide the most rigorous evidence. They demonstrate that founder replacement causally improves exit outcomes. The effect is strongest when C-level founders are replaced and leave the firm. Their study represents an important advance. It moves beyond correlational evidence to identify a specific mechanism through which VCs add value.

However, the scope of their analysis leaves substantial terrain unexplored. First, their outcome focus is narrow. They examine exit likelihood and exit valuations but do not analyse total capital raised, per-round funding, failure risk, or time to exit. These outcomes matter considerably to entrepreneurs navigating growth decisions. Second, their sample is restricted to U.S. firms. It remains unclear whether similar patterns hold in European ecosystems, where capital markets, acquisition pipelines, and norms around founder control differ. Third, they do not examine industry heterogeneity in detail. There are theoretical reasons to expect that founder-specific human capital is differentially valuable in technically complex sectors like Artificial Intelligence.

This thesis addresses these gaps through a descriptive, multi-outcome, and cross-context analysis. Using a novel dataset of venture-backed firms with manually validated CEO classifications, it compares founder- and professional-led startups across multiple performance dimensions. The study distinguishes IPOs from acquisitions and tests for industry-specific patterns. Rather than replicating Ewens and Marx's approach, it provides a broader empirical mapping of where and how performance differs by CEO type. This documents patterns that their design could not capture and generates descriptive benchmarks for future causal work.

3. Hypotheses Development

3.1 CEO Type and Funding Outcomes

Securing external capital is a fundamental milestone for scaling startups. The theoretical perspectives discussed above suggest that professional CEOs may be perceived by investors as reducing execution and monitoring risks. Their established track records in investor relations and financial reporting can enhance confidence and facilitate access to larger funding pools (Hsu 2007; Gompers et al. 2019). Founders, despite their product expertise, may be seen as less experienced in formal governance and financial management.

However, this pattern may not hold uniformly across industries. In technically complex sectors like Artificial Intelligence, deep domain knowledge is essential. Investors may rely more heavily on founder credibility and technical reputation when evaluating such ventures. Founder CEOs may therefore offer unique value signals that professional managers cannot easily replicate (Eesley and Roberts 2012; Pisano 2006).

Hypothesis 1: Professional-led startups raise more total external funding than founder-led startups, controlling for firm characteristics.

Hypothesis 1a: In the Artificial Intelligence sector, founder-led startups raise more total funding than professional-led startups.

3.2 CEO Type and Exit Outcomes

Exit events represent the primary means through which investors realise returns. Ewens and Marx (2018) provide causal evidence that founder replacement increases the likelihood of high-quality exits in U.S. firms. However, this thesis differs in important respects. It examines CEO type at observation rather than the dynamic event of replacement. It also extends beyond U.S. firms to include European markets.

Exit opportunities depend heavily on ecosystem conditions. Capital market depth, acquisition pipelines, and regulatory frameworks vary across countries. These structural factors may overshadow firm-level leadership characteristics (Kenney and Zysman 2016). Given this ecosystem variation and the methodological differences from Ewens and Marx, there is no strong theoretical basis to predict a systematic exit advantage for either leadership type.

Hypothesis 2: Founder-led startups and professional-led startups do not differ systematically in their likelihood of achieving an exit.

3.3 CEO Type and Failure Outcomes

Failure represents a critical but less frequently analysed dimension of startup performance. The theoretical arguments reviewed earlier suggest that founders may face elevated early-

stage failure risk. Limited managerial experience and potential escalation of commitment could contribute to operational breakdowns. Chen and Thompson (2015) provide supporting evidence. Founder-led firms exhibit greater short-term instability even when surviving firms eventually perform well.

Professional CEOs may introduce more structured decision-making and stricter financial oversight. This could reduce early operational failures.

Hypothesis 3: Founder-led startups face a higher likelihood of failure compared to professional-led startups.

4. Data & Methodology

4.1 Research Design

The empirical design is observational. Leadership origin is not randomly assigned, so the analysis cannot eliminate unobserved heterogeneity or isolate exogenous variation in CEO type. The strategy focuses on documenting conditional associations between CEO origin and multiple performance outcomes while reducing confounding through careful sample construction and extensive controls.

Several design choices support this approach. First, CEO-level information was manually collected and validated, reducing misclassification risk common in archival datasets. Second, sample construction applies consistent criteria across industries and countries. Third, regression models include firm-level, CEO-level, industry, and country controls. Fourth, interaction terms test whether associations vary across contexts rather than assuming uniform relationships. Fifth, survival models accommodate censoring and heterogeneous observation windows. These steps do not resolve endogeneity but substantially reduce confounding.

4.2 Data and Sample Construction

The data combine archival information from Crunchbase with hand-collected CEO characteristics. The initial dataset comprised all firms founded between 1 January 2005 and

31 December 2019. The end date ensures sufficient time for outcomes to materialise before COVID-19 introduced external shocks.

Several restrictions were applied. First, only firms headquartered in the United States and Europe were retained. This captures major venture ecosystems while preserving institutional variation. Second, only venture-backed startups were included (firms that secured at least one external funding round) because such companies operate under comparable governance pressures. Third, only the primary CEO at data extraction was retained. Fourth, CEO type was manually coded as founder or professional based on leadership histories. Finally, firms that had neither exited nor failed by the end of 2019 were treated as right-censored in survival models.

These procedures yield a final sample of 7,143 startups. This includes 967 exits and 132 confirmed failures. Approximately 1,500 CEOs were manually reviewed. Of these, 963 provided sufficient data to measure prior professional experience.

A reduced subsample of 963 firms with CEO experience data is used for robustness checks. Collecting experience for all CEOs would have required disproportionate manual effort with limited benefit. The subsample enables evaluation of whether human capital differences drive main results. Consistency across both samples strengthens the findings. For further information, see Appendix E, Section E.1.

4.3 Variable Definitions

Explanatory variable. CEO type is coded as 1 for founder CEOs and 0 for professional CEOs. This classification was manually validated. CEO experience is measured by the years of professional work prior to joining the startup. It is available for a subset of firms and used in robustness checks. CEO tenure captures total years the CEO has led the firm.

Funding outcomes. Total funding raised is log-transformed to address right skew. Number of funding rounds is included as a control.

Exit outcomes. A binary indicator captures whether an event is an IPO or an acquisition. Exit date and valuation measures are recorded where available. IPO valuation and acquisition price are log-transformed.

Failure. A binary indicator equals 1 if the firm permanently ceased operations without an exit. Closure dates were manually validated where possible.

Controls. Firm age, CEO gender, country fixed effects, and industry fixed effects are included in all specifications. Interaction terms test for moderation by industry and other factors. For further information, see Appendix C and Appendix E in E.2.

4.4 Statistical Models

Different models match the statistical properties of each dependent variable.

OLS regression is used for continuous outcomes such as total funding and exit valuations. Log transformation addresses skewness and stabilises variance. OLS provides interpretable semi-elasticities for log-transformed dependent variables (Wooldridge 2013).

Logistic regression is used for binary outcomes such as exit occurrence and failure. Logistic models are suited for dichotomous variables and permit interaction terms. Given the rarity of failure events, interpretation focuses on coefficient magnitude and direction rather than classification accuracy (Wooldridge 2013; Therneau and Grambsch 2000).

Cox proportional hazards models are used for time-to-event outcomes such as time to exit. These models accommodate right-censoring and do not require specifying a functional form for the baseline hazard (Cox 1972). Proportional hazards assumptions were examined using Schoenfeld residuals.

4.4.1 Model Specifications

This section presents the econometric specifications used to estimate the association between CEO type and startup outcomes. All continuous monetary variables are log-transformed to

reduce skewness and facilitate interpretation as approximate percentage differences.

Funding Models

The baseline specification for total funding raised is:

$$\log(Funding_i) = \beta_0 + \beta_1 FounderCEO_i + \beta_2 X_i + \gamma_c + \varepsilon_i \quad (1)$$

where Xi is a vector of firm and CEO controls including Age, Male, Tenure, and Rounds. The coefficient β1 captures the conditional association between founder-CEO status and log funding.

Exit likelihood is estimated using logistic regression; time-to-event outcomes use Cox proportional hazards models; and exit valuations are estimated using OLS on the subset of firms with observed outcomes. Full model specifications, including industry interaction models for funding, exit, failure, and valuation outcomes, are provided in Appendix F. Variable definitions are summarised in Table 1.

Table 1: Variable Definitions

Variable	Definition
$Funding_i$	Total funding raised by firm i in USD
$FounderCEO_i$	Indicator equal to 1 if firm i has a founder-CEO, 0 otherwise
Age_i	Firm age in years at observation
$Male_i$	Indicator equal to 1 if CEO is male, 0 otherwise
$Tenure_i$	CEO tenure in years
$Rounds_i$	Number of funding rounds completed
$Experience_i$	CEO years of professional experience prior to joining startup
$Exit_i$	Indicator equal to 1 if firm achieved IPO or acquisition, 0 otherwise
$Failure_i$	Indicator equal to 1 if firm ceased operations without exit, 0 otherwise
γ_c	Country fixed effects (reference: other countries)
δ_j	Industry fixed effects (reference: other industries)

4.5 Identification Logic and Limitations

The analysis controls for many relevant variables but cannot guarantee causal inference. CEO type reflects joint decisions by founders, boards, and investors. These decisions are shaped by unobserved factors such as founder ability, investor quality, and venture risk. Results should be interpreted as associations conditional on observables rather than causal effects.

Several specific limitations merit acknowledgement. Survivorship bias is inherent in Crunchbase data because failures are underreported. Manual verification improves accuracy but cannot fully correct this. Missing CEO experience data introduces selection concerns, addressed by treating experience models as robustness checks. Right-censoring affects time-to-event outcomes, though Cox models provide an appropriate remedy. More information is provided in Appendix E, Section E.3.

5. Results

5.1 Funding Outcome

The relationship between CEO type and total capital raised is evaluated using OLS regression with log-transformed total funding as the dependent variable. In the full sample, the coefficient on Founder CEO is negative and significant ($B = –0.108$, $p < .01$). This corresponds to approximately 10% lower total funding for founder-led firms compared to otherwise similar professional-led firms.

The subsample with CEO experience data ($n = 963$) provides a robustness check. CEO experience is positively associated with total funding ($B = 0.034$, $p < .001$). Each additional year of prior experience corresponds to roughly a 3.4% increase in funding. Controlling for experience, the funding gap widens: the Founder CEO coefficient increases to –0.210 ($p = 0.053$), corresponding to approximately 19% lower funding. Although marginally significant, this suggests that observable human capital differences do not explain the professional-CEO funding advantage; if anything, accounting for experience strengthens the pattern. These results support H1.

The industry interaction model reveals one significant exception. The interaction between Founder CEO and Artificial Intelligence is positive and significant ($B = 0.281$, $p = 0.027$). Within AI, founder-led firms raise more capital than professional-led firms. No other industry interaction reaches significance. This supports H1a.

Table 2: Determinants of Total Funding Raised (OLS)

	(1) Full Sample	(2) With Experience	(3) Industry Int.
Founder CEO	−0.108**	−0.210†	−0.117*
	(0.040)	(0.108)	(0.052)
CEO Experience	—	0.034***	—
		(0.006)	
Founder CEO × AI	—	—	0.281*
			(0.127)
Company Age	0.099***	0.047*	0.083***
	(0.009)	(0.019)	(0.006)
Funding Rounds	0.338***	0.290***	0.331***
	(0.008)	(0.022)	(0.008)
Male CEO	0.418***	0.489**	0.426***
	(0.060)	(0.175)	(0.060)
US Dummy	1.169***	1.002***	1.180***
	(0.051)	(0.133)	(0.051)
Country FE	Yes	Yes	Yes
Industry FE	No	No	Yes
N	7,143	963	7,143
Adj. R^2	0.344	0.327	0.352

*Notes: Dependent variable is log(total funding USD). Standard errors in parentheses. †p < .10, *p < .05, **p < .01, ***p < .001.*

The mixed-effects model analysing funding per round shows no systematic difference by CEO type. The dominant predictors are geography and firm maturity. U.S.-based startups raise larger rounds. Older firms obtain higher average round sizes. Founder status explains little additional variance (Appendix D in D.1).

5.2 Exit Outcomes

Exit likelihood is analysed using logistic regression with a binary indicator for IPO or acquisition. Time-to-exit is examined using Cox proportional hazards models.

Table 3: Exit Models

	(1) Baseline	(2) Industry Effects	(3) Time to Exit
	(Logistic)	(Logistic)	(Cox PH)
Founder CEO	−0.022	0.199	−0.131
	(0.082)	(0.243)	(0.282)
[OR / HR]	[0.98]	[1.22]	[0.88]
Company Age	0.262***	0.249***	−0.150*
	(0.017)	(0.012)	(0.062)
Male CEO	0.128	0.171	-0.557
	(0.135)	(0.136)	(0.399)
Funding Rounds	−0.021	−0.021	0.055
	(0.015)	(0.015)	(0.044)
US Dummy	0.683***	0.807***	0.104
	(0.125)	(0.209)	(0.354)
Biotechnology	—	0.608***	—
		(0.125)	
[OR]		[1.84]	
Financial Services	—	−0.335*	—
		(0.166)	
AI	—	0.019	—
		(0.135)	
Commerce	—	−0.202	—
		(0.142)	
Country FE	Yes	Yes	Yes
Industry FE	No	Explicit	No
Country × Founder	No	Yes	No
N	7,120	7,132	890
Pseudo R^2 / χ^2	0.160	0.169	33.71***

*Notes: OR = odds ratio; HR = hazard ratio. Standard errors in parentheses. Sample sizes vary due to listwise deletion of missing values. Model 2 includes country × founder interactions (all non-significant, see Appendix D). †p < .10, *p < .05, **p < .01, ***p < .001.*

CEO type shows no significant association with exit likelihood (B = −0.022, p = .794, OR = 0.98). This null finding persists when industry effects and country × founder interactions are included (B = 0.199, p = .413). Notably, biotechnology firms exhibit significantly higher exit likelihood than other industries (B = 0.608, p < .001, OR = 1.84), while financial services

firms show lower exit odds (B = −0.335, p = .044). The founder effect does not vary by country; none of the country × founder interactions reach significance. Other covariates show stronger relationships. Firm age is positively associated with exit. U.S.-based startups have significantly higher exit odds than firms elsewhere. This supports H2.

Time to exit shows similar patterns. The hazard ratio for Founder CEO is 0.88 (p = 0.642). Founder-led and professional-led firms reach exits at similar speeds. Firm age is associated with slightly slower exits (HR ≈ 0.86). Country effects are limited and do not reach conventional significance.

5.3 Failure Outcomes

Failure is analysed using logistic regression with a binary indicator for firm closure without exit. Time-to-failure is examined using Cox proportional hazards models. Table 4 reports results from the subsample with CEO experience data, providing a conservative test that controls for observable human capital differences.

Table 4: Failure Models

	Failure Likelihood (Logistic)	**Time to Failure** (Cox PH)
Founder CEO	0.666*	0.582*
	(0.292)	(0.286)
[OR / HR]	[1.95]	[1.79]
CEO Experience	−0.025	−0.025†
	(0.016)	(0.015)
Company Age	0.087†	−0.115*
	(0.048)	(0.057)
Funding Rounds	−0.079†	−0.079
	(0.057)	(0.056)
US Dummy	1.157**	1.161**
	(0.418)	(0.433)
Country FE	Yes	Yes
N	961	949
Pseudo R^2 / χ^2	0.123	45.99***

*Notes: Restricted to subsample with CEO experience data. OR/HR in brackets. Standard errors in parentheses. Sample sizes vary due to listwise deletion of missing values. †p < .10, *p < .05, **p < .01, ***p < .001.*

Founder-led startups face substantially higher failure risk. In the model with CEO experience controls, the Founder CEO coefficient is positive and significant (B = 0.666, p = 0.023, OR = 1.95). Founder-led firms have nearly twice the odds of failure as professional-led firms. This supports H3.

The Cox survival model confirms this pattern. The hazard ratio for Founder CEO is 1.79 (p = 0.042). Founder-led ventures fail at a faster rate.

Failure risk declines sharply with firm age. The hazard is concentrated in the early years of venture development. Country effects show elevated failure hazards for U.S. and German startups relative to other countries.

5.4 Valuation Outcomes

Exit valuations are examined separately for IPOs and acquisitions.

Table 5: Exit Valuation Models

	(1) IPO Valuation	(2) Acq. Price	(3) IPO w/ Industry	(4) Acq. w/ Industry
Founder CEO	0.804**	0.203	0.778*	0.312
	(0.269)	(0.248)	(0.380)	(0.229)
[exp(β)]	[2.23×]	[1.23×]	[2.18×]	[1.37×]
Company Age	0.022	0.008	−0.006	0.018
	(0.064)	(0.049)	(0.044)	(0.037)
Funding Rounds	0.175***	0.132**	0.156***	0.140**
	(0.036)	(0.044)	(0.044)	(0.044)
Male CEO	0.710*	0.372	0.495	0.466
	(0.348)	(0.418)	(0.375)	(0.421)
US Dummy	1.553**	−0.151	1.820***	−0.244
	(0.501)	(0.429)	(0.453)	(0.428)
AI Industry	—	—	0.748	−0.669
			(0.939)	(0.408)
Commerce Industry	—	—	0.045	−1.126*
			(0.968)	(0.463)
Biotech Industry	—	—	0.004	0.330
			(0.340)	(0.348)
Country FE	Yes	Yes	Yes	Yes
Industry FE	No	No	Explicit	Explicit
N	126	228	126	228
Adj. R^2	0.316	0.069	0.332	0.090

*Notes: Dependent variables are log(valuation/price) in USD. exp(β) shows implied multiplier. Standard errors in parentheses. Sample sizes vary due to listwise deletion of missing values. †p < .10, *p < .05, **p < .01, ***p < .001.*

IPO valuations

Among 126 firms with complete IPO data, founder-led firms achieve substantially higher valuations. The Founder CEO coefficient is positive and significant ($B = 0.804$, $p = 0.003$). This corresponds to IPO valuations more than twice as large for founder-led firms ($\exp(0.804) \approx 2.23$).

This founder premium is notable given earlier findings. Founder-led firms raise less capital and fail more often. Yet those reaching public markets command higher valuations.

Other covariates show expected patterns. U.S.-based firms have markedly higher IPO valuations ($B = 1.553$, $p < 0.01$). The number of funding rounds is positively associated with IPO valuation. CEO tenure and firm age are not significant. Extended models with industry interactions show the founder premium persists across sectors.

Acquisition valuations

Acquisition valuations show a different pattern. Among 228 firms with observed prices, CEO type is not significantly associated with deal value. The Founder CEO coefficient is small and insignificant ($B = 0.203$, $p = 0.413$).

The number of funding rounds is the strongest predictor of acquisition valuation. Country effects and CEO characteristics are not consistently significant.

6. Discussion

The empirical analyses document systematic associations between CEO origin and several startup outcomes. Because leadership is not randomly assigned, these patterns should be understood as conditional associations rather than causal effects. This section interprets the findings, considers alternative explanations, and situates the results relative to existing causal evidence.

6.1 Summary of Empirical Patterns

The results reveal a nuanced picture of how founder-led and professional-led startups differ.

For funding, professional-led startups raise approximately 10% more total capital in the baseline specification, increasing to 19% when controlling for CEO experience. This pattern holds across specifications. However, in the field of Artificial Intelligence, founder-led firms raise more capital than professional-led firms. This sector-specific reversal is the only significant industry interaction.

Exit outcomes show no systematic difference between founder-led and professional-led startups in likelihood or timing. Country and industry effects dominate. U.S.-based firms and Biotechnology firms are more likely to exit. Financial Services firms are less likely to exit. CEO type adds little explanatory power.

In founder-led startups, failure rates are nearly twice those of professional-led startups. This elevated risk is concentrated in early years. The pattern is robust across logistic and survival specifications.

Regarding valuations, founder-led firms that reach an IPO achieve valuations more than twice those of comparable professional-led firms. Acquisition valuations show no difference by CEO type.

These patterns create an apparent tension. Founder-led firms raise less capital and fail more often. Yet the subset that reaches IPO commands substantially higher valuations. Understanding this tension requires considering alternative interpretations.

6.2 Interpreting the Findings: Causal vs. Selection Mechanisms

Two broad interpretations are consistent with the observed patterns. Distinguishing between them is essential for drawing appropriate conclusions.

Leadership-mechanism interpretation

One reading is that CEO type causally influences outcomes through differences in skills, behaviours, and capabilities. Under this interpretation, professional CEOs may be better at activities emphasising operational discipline and capital access. Their experience with

investor relations, financial reporting, and organisational scaling may directly improve fundraising outcomes and reduce failure risk. Founders, by contrast, may add value through vision, technical credibility, and narrative attributes that public market investors reward at IPO.

This interpretation aligns with theoretical arguments about founder versus professional human capital (Wasserman 2009; Hellmann and Puri 2002). It also resonates with Ewens and Marx's (2018) causal finding that replacing founders with professional executives improves exit outcomes. Under this view, the patterns reflect genuine differences in what each leader type contributes.

Selection interpretation

An alternative reading is that CEO type primarily reflects underlying differences in ventures and investors rather than causing outcomes directly. Under this interpretation, professional CEOs disproportionately join firms that already exhibit stronger traction, more experienced backers, or more scalable business models. These characteristics (not the CEO's leadership) drive higher funding and lower failure rates.

Similarly, founders who remain in charge may systematically pursue riskier or more exploratory strategies. This would produce both higher failure rates and a positively selected subset of successful firms. The IPO valuation premium may not reflect founder leadership per se, but rather the exceptional quality of founder-led firms that survive the higher early-stage mortality.

Investor selection reinforces this logic. Sophisticated VCs may install professional CEOs in firms they view as promising but operationally challenged. They may leave founders in place when technical credibility is paramount or when the founder is exceptionally capable. CEO type thus becomes a signal of investor assessments rather than an independent driver of outcomes.

Limitations of the Empirical Design

The empirical design cannot definitively separate these interpretations. Several features of the analysis reduce but do not eliminate selection concerns. The models control for firm age, funding history, industry, and country. The robustness checks with CEO experience show that observable human capital differences do not fully explain the patterns. The consistency across specifications suggests the associations are not fragile.

However, unobserved factors remain. Founder ability, investor quality, board composition, and venture risk are not directly measured. CEO type reflects joint decisions by founders, boards, and investors. These decisions are shaped by private information about firm prospects. Without exogenous variation in CEO assignment, causal claims are not warranted.

The safest conclusion is that the results reveal robust empirical patterns in how founder-led and professional-led startups differ. The exact mechanisms of whether causal leadership effects, selection, or both remain open for investigation with quasi-experimental designs.

6.3 Relation to Ewens and Marx

Ewens and Marx (2018) provide the cleanest causal evidence on founder replacement (see Section 2.5), showing that replacement improves exit outcomes, particularly when C-level founders leave entirely. Their study and this thesis address related but distinct questions. Ewens and Marx examine the causal effect of a specific governance intervention, investor-driven founder replacement in one institutional setting. This analysis compares founder-led and professional-led firms across multiple outcomes, industries, and countries without attempting causal identification.

The findings are broadly complementary. Ewens and Marx show that replacement can improve exits. The findings here show that professional-led firms raise more capital and fail less often, patterns consistent with professional leadership providing operational benefits. The

AI exception and IPO valuation premium, however, suggest that founder leadership retains value in specific contexts that Ewens and Marx's design could not examine.

One difference merits attention. Ewens and Marx find that naïve regressions show a negative correlation between replacement and exit success. This reflects selection: VCs replace founders in struggling firms. Instrumented regressions reverse the sign, revealing a positive causal effect. This thesis relies on observational associations without instrumentation. The professional funding advantage and founder failure disadvantage could partly reflect similar selection dynamics. Professional CEOs may join stronger firms. Founder-led firms may be riskier on average.

The IPO valuation premium is harder to explain solely through selection. If founder-led firms reaching IPO were simply survivors of a high-risk pool, one might expect valuations similar to or lower than those of other firms, not a twofold premium. This pattern hints at genuine founder value, perhaps in vision, narrative, or innovation that public markets recognise. However, even this interpretation requires caution. Founders who navigate the full path to IPO may be exceptional individuals whose success reflects personal ability rather than founder status per se.

6.4 Practical Implications

Despite the interpretive limitations, the findings offer provisional guidance for founders, investors, and boards. These implications should be understood as informed by associations, not proven causal effects.

For founders

The higher failure rates observed among founder-led firms suggest that early-stage ventures may be particularly vulnerable when governance and operational capabilities are underdeveloped. Founders might consider strengthening the management team through experienced hires in finance, operations, or sales. Sharing leadership responsibilities with a

seasoned executive may reduce the risk of early failure without requiring founders to exit the CEO role entirely.

At the same time, the IPO valuation premium suggests that maintaining visible founder involvement can be valuable when the long-term goal is a public listing. Founders should weigh the benefits of professionalisation against the potential costs of diluting their leadership narrative.

For investors and boards

The evidence argues against simple rules. Professional CEOs are associated with better fundraising and lower failure. Yet founder-led firms that reach IPO command substantial valuation premiums. A nuanced approach would match leadership structure to the firm's primary bottleneck at each stage.

Early-stage firms facing operational challenges may benefit from professional leadership or strong operational hires. Firms in technically complex sectors, such as AI, may benefit from retaining founder credibility. Hybrid arrangements, such as a professional CEO with the founder as chair or chief product officer, may capture the benefits of both leadership types.

Ewens and Marx's causal evidence supports activist intervention when firms struggle. This thesis adds that such intervention may carry costs if it undermines founder-driven advantages in narrative and vision. Boards should consider not only whether to replace founders but also how to preserve founder contributions in alternative roles.

For ecosystem stakeholders

The strong country effects in exit outcomes underscore a simple point. Leadership configurations cannot compensate for weak structural conditions. Deep capital markets, active acquisition pipelines, and supportive regulatory environments matter more for aggregate exit rates than whether individual firms are led by founders or professionals. Policies that

strengthen these ecosystem features are likely to have a greater impact than interventions targeting CEO type directly.

7. Conclusion

This thesis provides a comprehensive descriptive analysis of how founder-led and professional-led startups differ, documenting systematic patterns that complement existing causal evidence on founder replacement.

The findings reveal that the same leadership arrangement can be beneficial on some dimensions and neutral or detrimental on others. Professional-led startups raise more capital and experience lower failure rates. Founder-led startups show no disadvantage in exit likelihood or timing but face elevated early-stage mortality. Yet founder-led firms that reach IPO achieve a substantial valuation premium over professional-led firms. In Artificial Intelligence, the typical professional funding advantage reverses, as founder-led AI firms raise more capital than their professional-led counterparts.

These patterns do not lend themselves to simple interpretation. Professional leadership appears associated with operational stability and investor confidence, while founder leadership is linked to higher risk but also higher rewards among survivors. Whether these associations reflect causal effects of leadership or selection of different leader types into different ventures cannot be determined from observational data alone. The analysis has shown that the patterns are robust to extensive controls and hold across multiple specifications. It has not established causality.

Relative to Ewens and Marx (2018), this thesis offers complementary breadth. It examines outcomes they did not analyse: total funding, failure risk, IPO versus acquisition valuations. It extends geographic scope to European ecosystems. It documents industry heterogeneity, particularly the distinctive patterns in Artificial Intelligence. Together, the two studies suggest that professional leadership can add value through operational discipline while founder

leadership retains value through vision, credibility, and narrative, especially in technically complex sectors and public market contexts.

Several avenues merit future research. Quasi-experimental designs exploiting exogenous shocks to CEO assignment, similar to Ewens and Marx's non-compete instrument, could help identify causal effects across the broader outcome set examined here. Richer data on founding teams, board composition, and investor characteristics could illuminate the selection mechanisms that shape CEO choice. Extending the analysis to additional ecosystems and emerging sectors would clarify how structural conditions moderate the value of different leadership types.

The practical question is not whether founders or professional CEOs are better in general. It is when, where, and under what conditions each type creates value. Ben Horowitz, whose experience of being dismissed as not a "real CEO" opened this thesis, later reflected on this tension: "Founder CEOs don't know how to be CEOs, but it doesn't mean they can't learn. The question is... can the founder learn that job and can they tolerate all the mistakes they will make doing it?" (Horowitz 2014). The higher failure rates documented here suggest many cannot. Yet the IPO valuation premium shows that those who do learn command exceptional rewards. The founder-versus-professional debate will continue. It should be a debate about fit, timing, and context not about which type is universally superior.

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Appendix A: Descriptive Statistics

Table A1 summarises the main variables used in the analysis. The dataset includes 7,143 venture-backed startups founded between 2005 and 2019 in North America and Europe. Firm age ranges from 0 to 14 years (M = 6.36). Funding intensity varies substantially: firms raised between 1 and 42 funding rounds (M = 3.71). CEO experience is available for a subsample of 963 firms, averaging 15.6 years. Event-history variables show considerable heterogeneity, with time to failure averaging 2,668 days and time to exit averaging 2,235 days.

Table A1: Summary Statistics

Variable	N	Min	Max	Mean	SD
Company Age (years)	7,143	0.00	14.00	6.36	3.25
Funding Rounds	7,143	1	42	3.71	2.34
Log Total Funding (USD)	7,143	9.19	23.93	16.20	1.81
CEO Experience (years)	963	0	45	15.63	8.83
CEO Tenure (years)	7,143	0.42	17.01	6.34	3.02
Time to Failure (days)	7,086	0	5,477	2,668	1,186
Time to Exit (days)	6,682	0	5,360	2,235	1,136

Appendix B: Sample Composition

B.1 Geographic Distribution

The sample is concentrated in the United States (65.4%), reflecting the global dominance of U.S. venture capital markets. The United Kingdom represents the second-largest group (9.8%), followed by Canada, Germany, and France (each approximately 3-4%). This distribution should be considered when interpreting country-level effects.

Table B1: Country Distribution

Country	N	Percent
United States	4,669	65.4%
United Kingdom	702	9.8%
Canada	266	3.7%
Germany	263	3.7%
France	217	3.0%
Other	1,026	14.4%
Total	**7,143**	**100%**

B.2 Industry Distribution

The six industries included as dummy variables in the regression analyses Artificial Intelligence, Commerce & Shopping, Apps, Financial Services, Data & Analytics, and Biotechnology together represent approximately 49% of all firms. Their inclusion reflects both their substantial presence in the dataset and their theoretical relevance for explaining variation in funding, exit, and valuation outcomes.

Table B2: Industry Distribution

Industry	N	Percent
Artificial Intelligence	787	11.0%
Commerce & Shopping	640	9.0%
Apps	557	7.8%
Financial Services	549	7.7%
Data & Analytics	493	6.9%
Biotechnology	482	6.7%
Other Industries	3,635	50.9%
Total	**7,143**	**100%**

B.3 Outcome Distribution

The majority of firms (84.6%) remain operating at the end of the observation period. Successful exits (IPO or acquisition) account for 13.5% of the sample, with acquisitions (11.8%) far more common than IPOs (1.8%). Confirmed failures represent 1.8% of the sample, though these likely underestimate true failure rates due to survivorship bias in venture databases.

Table B3: Outcome Distribution

Outcome	N	Percent
Still Operating	6,044	84.6%
Exit (IPO or Acquisition)	967	13.5%
IPO	126	1.8%
Acquisition	841	11.8%
Closed/Failed	132	1.8%
Total	**7,143**	**100%**

Appendix C: Variable Definitions and Measurement

This appendix provides detailed definitions of all variables used in the empirical analysis. See Section 4.3 in the main text for a discussion of measurement choices and potential limitations.

Table C1: Variable Definitions

Variable	Definition
Dependent Variables	
Total Funding	Sum of all funding raised across all rounds, in USD (log-transformed)
Exit	Binary indicator: 1 if firm achieved IPO or acquisition, 0 otherwise
Failure	Binary indicator: 1 if firm permanently ceased operations without exit, 0 otherwise
IPO Valuation	Market capitalization at IPO, in USD (log-transformed)
Acquisition Price	Reported acquisition deal value, in USD (log-transformed)
Key Independent	
Founder CEO	Binary indicator: 1 if CEO was a founder of the company, 0 if professional (non-founder) CEO
Control Variables	
Company Age	Years since founding at time of observation
Male CEO	Binary indicator: 1 if CEO is male, 0 if female
CEO Tenure	Years the current CEO has held the position
CEO Experience	Years of professional experience prior to current role (available for n = 963)
Funding Rounds	Count of completed funding rounds
Fixed Effects	
Country FE	Indicators for US, UK, Germany, France, Canada (reference: other countries)
Industry FE	Indicators for AI, Biotech, FinTech, Commerce, Apps, Data & Analytics (reference: other)

C.1 CEO Classification Procedure

The key independent variable Founder CEO status required careful classification to distinguish between founder-led and professionally-managed startups. The classification procedure followed a systematic multi-step approach.

Primary classification relied on Crunchbase's founder and executive databases. A CEO was classified as a founder-CEO if they appeared in both the company's founder list and current CEO position. Conversely, a CEO was classified as professional if they held the CEO title but did not appear among the founding team.

For ambiguous cases such as early employees promoted to CEO, or co-founders who joined shortly after incorporation secondary sources were consulted. LinkedIn profiles provided employment history to verify founding involvement. Company websites and press releases offered additional confirmation of founder status. In cases where founding involvement remained unclear after consulting multiple sources, the firm was excluded from the sample to avoid measurement error.

Edge cases were handled as follows: (1) CEOs who were founding team members but not equity founders were classified as founders if they joined within the first six months; (2) Interim CEOs serving less than one year were excluded; (3) In cases of CEO transitions during the observation period, the CEO at the time of the most recent funding round was used for classification.

Appendix D: Robustness Checks

This appendix presents supplementary analyses testing the robustness of the main findings to alternative specifications, interaction effects, and sample restrictions.

D.1 Per-Round Funding Analysis

Table D1 examines funding at the round level rather than total funding. The negative coefficient on Founder CEO (B = −0.330, p < .001) indicates that founder-led firms raise approximately 28% less per round, consistent with the main findings.

Table D1: Funding Amount per Round

	Amount per Round
Variable	(OLS)
Founder CEO	−0.330***
	(0.028)
CEO Tenure at Round	0.167***
	(0.006)
Company Age	−0.008
	(0.005)
US Dummy	1.215***
	(0.040)
Country FE	Yes
N	11,735
Adj. R^2	0.209

*Notes: Unit of analysis is funding round (n = 11,735 rounds). †p < .10, *p < .05, **p < .01, ***p < .001.*

D.2 Gender × CEO Type Interaction

Table D2 tests whether the association between CEO type and exit likelihood varies by CEO gender. The interaction term is not significant (B = 0.438, p = .120), suggesting no differential effect.

Table D2: Exit Likelihood with Gender Interaction

	Exit Likelihood
Variable	(Logistic)
Founder CEO	−0.392
	(0.272)
Male CEO	−0.113
	(0.224)
Founder CEO × Male	0.438
	(0.282)
Company Age	0.249***
	(0.012)
Country FE / Industry FE	Yes / Yes
N	7,132
Pseudo R^2	0.169

*Notes: †p < .10, *p < .05, **p < .01, ***p < .001.*

D.3 Country × Founder Interactions

Table D3 tests whether the founder effect varies across countries. None of the interaction terms reach significance, indicating that the (null) association between CEO type and exit is consistent across the US, UK, Germany, France, and Canada.

Table D3: Exit Likelihood with Country Interactions

	Exit Likelihood
Variable	(Logistic)
Founder CEO	0.199
	(0.243)
Founder CEO × US	−0.257
	(0.258)
Founder CEO × UK	0.013
	(0.390)
Founder CEO × Germany	0.250
	(0.569)
Founder CEO × France	−0.116
	(0.515)
Founder CEO × Canada	0.164
	(0.478)
Industry Effects	Yes (see Table 3)
Country FE	Yes
N	7,132
Model χ^2	706.02***
Pseudo R^2	0.169

*Notes: †p < .10, *p < .05, **p < .01, ***p < .001.*

Appendix E: Extended Methodology Notes

This appendix provides additional methodological details that extend the discussion in Sections 4.2, 4.3, and 4.5 of the main text.

E.1 Data and Sample Construction

The dataset was constructed using Crunchbase, a comprehensive database of venture-backed companies widely used in entrepreneurship research. The sample construction involved multiple stages of filtering, merging, and cleaning across several Crunchbase data tables.

Initial Data Extraction and Filtering

The raw Crunchbase organisations database contained approximately 800,000 entries. Initial filtering reduced this to approximately 80,000 firms by removing: (1) duplicate entries, (2) companies without valid UUID identifiers, (3) companies founded before 2005, (4) firms with no recorded total funding information, and (5) non-venture-backed companies. Geographic filtering further restricted the sample to North America and Europe, excluding Asian markets to maintain regional focus and comparability. This yielded approximately 60,000 potentially eligible firms.

Identifying Venture-Backed Companies

To verify venture capital backing within the 2005–2019 reference period, the organisations database was merged with Crunchbase's investors and funding rounds databases. This merge confirmed which companies received documented VC investment during the observation window, enabling precise identification of the target population.

Data Cleaning and UUID Reconciliation

The merging process revealed structural inconsistencies in UUID formatting across Crunchbase tables. These errors were systematically cleaned to enable successful dataset integration. After resolving UUID issues and completing the merge across organisations, funding rounds, and investor databases, 18,025 rows remained from the original 128,000 entries in the combined raw database.

CEO Information and Classification

The Crunchbase people database was filtered to retain only individuals classified as "Founder CEO" or "CEO." Of the 16,523 companies in the cleaned organisations list, 12,458 had the required CEO information available.

Manual Data Collection

For CEOs identified in the dataset, additional information was collected manually via LinkedIn to determine: (1) CEO start date at the company, (2) CEO end date (coded as ongoing for current CEOs), and (3) prior professional experience. Experience was operationalised as total years of professional work history to maintain consistency and avoid complications from incomplete LinkedIn data. This manual collection enabled the construction of CEO tenure variables and the experience subsample (n = 963).

Final Sample

After all filtering, merging, and cleaning procedures, the final analytical sample comprises 7,143 venture-backed startups founded between 2005 and 2019 in North America and Europe, with complete information on CEO type, funding history, and firm characteristics.

Step	Description	N
1	Raw Crunchbase organisations	~800,000
2	After removing duplicates, missing UUIDs, pre-2005, no funding, non-VC	~80,000
3	After geographic filtering (NA + Europe only)	~60,000
4	After merging with investors/funding rounds (VC-backed 2005–2019)	18,025
5	Companies with CEO information available	12,458
6	After final cleaning and validation	**7,143**

E.2 Variable Construction Details

Exit outcomes. A firm was classified as having achieved an exit if Crunchbase recorded either an IPO or acquisition event. IPO valuations were measured as market capitalization at the time of listing, obtained from Crunchbase. Acquisition prices were taken from Crunchbase's reported deal values; acquisitions with undisclosed prices were coded as exits but excluded from valuation analyses.

Failure outcomes. Failure was identified using Crunchbase's "closed" status indicator, supplemented by manual verification of company websites and news sources. A firm was coded as failed if it permanently ceased operations without achieving an exit. This definition excludes pivots, acqui-hires, and firms that simply stopped reporting to Crunchbase. The conservative coding likely underestimates true failure rates.

Funding variables. Total funding was calculated as the sum of all funding rounds recorded in Crunchbase, converted to USD. This includes seed, angel, Series A through late-stage rounds. All monetary variables were log-transformed to address right-skewness and facilitate interpretation as approximate percentage differences.

Industry classification. Industry categories were based on Crunchbase's primary industry tags. The six industries included as dummy variables (AI, Biotechnology, Commerce, Financial Services, Apps, Data & Analytics) were selected based on sample prevalence and theoretical relevance. Firms with multiple industry tags were assigned to their primary listed category.

E.3 Identification Strategy and Limitations

This study employs an observational research design that documents conditional associations between CEO type and startup outcomes. It is important to emphasize that the findings should not be interpreted as causal effects. Several identification challenges preclude causal inference.

Selection bias. The assignment of founder versus professional CEOs is not random. Firms that hire professional CEOs may differ systematically from founder-led firms in ways that also affect outcomes. For example, VCs may install professional CEOs in struggling firms (negative selection) or in high-potential firms ready to scale (positive selection). The direction and magnitude of this selection bias cannot be determined from observational data alone.

Reverse causality. The relationship between CEO type and outcomes may run in both directions. Poor performance might trigger founder replacement, creating an association between professional CEOs

and negative outcomes that reflects the consequence rather than the cause. Similarly, strong performance might allow founders to resist replacement pressure.

Omitted variable bias. Unobserved factors may drive both CEO selection and outcomes. Founder human capital, board composition, investor quality, and market timing are difficult to measure but likely correlated with both the independent and dependent variables. While the models include extensive controls, residual confounding cannot be ruled out.

Ewens and Marx (2018) address these identification challenges using an instrumental variables approach, exploiting state-level variation in non-compete agreement enforceability as an exogenous shock to the supply of professional executives. Their findings that founder replacement improves performance differ from the null results on exit likelihood reported here, highlighting how methodological differences can lead to divergent conclusions.

This study's contribution is therefore descriptive rather than causal. The findings document conditional associations that characterize the venture-backed startup population, providing a foundation for theory development and identifying patterns that warrant further investigation with methods better suited to causal inference.

Future research could strengthen causal identification through: (1) instrumental variables exploiting exogenous variation in CEO supply or demand; (2) regression discontinuity designs around funding thresholds that trigger CEO changes; (3) difference-in-differences approaches comparing firms before and after CEO transitions; or (4) matching methods that construct comparable founder-led and professional-led firm pairs. Each approach involves tradeoffs between internal validity and generalizability.

Appendix F: Model Specifications

This appendix presents the full econometric specifications used to estimate the association between CEO type and startup outcomes. All continuous monetary variables are log-transformed to reduce skewness and facilitate interpretation as approximate percentage differences.

F.1 Funding Models

The baseline specification for total funding raised is:

$$\log(Funding_i) = \beta_0 + \beta_1 FounderCEO_i + \beta_2 X_i + \gamma_c + \varepsilon_i \qquad (1)$$

where X_i is a vector of firm and CEO controls including *Age*, *Male*, *Tenure*, and *Rounds*; and γ_c denotes country fixed effects. The coefficient β_1 captures the conditional association between founder-CEO status and log funding.

To test whether the funding association varies across industries (H1a), the model is extended with industry fixed effects and interaction terms:

$$\log(Funding_i) = \beta_0 + \beta_1 FounderCEO_i + \beta_2 X_i + \Sigma_j \beta_j (FounderCEO_i \times Industry_j) + \gamma_c + \delta_j + \varepsilon_i \quad (2)$$

where δ_j denotes industry fixed effects.

F.2 Exit Models

Exit likelihood is estimated using logistic regression:

$$\Pr(Exit_i = 1) = \Lambda(\beta_0 + \beta_1 FounderCEO_i + \beta_2 X_i + \gamma_c) \qquad (3)$$

where $\Lambda(\cdot)$ denotes the logistic function. Coefficients are reported as log-odds; odds ratios are obtained by exponentiation. Extended models add industry fixed effects (δ_j) and country × founder interaction terms.

Time to exit is modelled using Cox proportional hazards:

$$h_i(t) = h_0(t) \cdot \exp(\beta_1 FounderCEO_i + \beta_2 X_i + \gamma_c) \qquad (4)$$

where $h_i(t)$ is the hazard of exit for firm i at time t and $h_0(t)$ is the baseline hazard. Hazard ratios greater than 1 indicate faster exit. The proportional hazards assumption was tested using Schoenfeld residuals.

F.3 Failure Models

Failure likelihood and time to failure are estimated using specifications analogous to equations (3) and (4), substituting *Failure* for *Exit* as the dependent variable. These models are restricted to the subsample with CEO experience data (n = 961 for likelihood; n = 949 for time to failure) and include *CEO Experience* as an additional control.

F.4 Valuation Models

Exit valuations are estimated using OLS on the subset of firms with observed outcomes:

$$\log(Valuation_i) = \beta_0 + \beta_1 FounderCEO_i + \beta_2 X_i + \gamma_c + \varepsilon_i \qquad (5)$$

where $Valuation_i$ is either IPO market capitalisation (n = 126) or acquisition price (n = 228). The coefficient β_1 represents the log-difference in valuation between founder-led and

professional-led firms; $\exp(\beta_1)$ gives the implied multiplier. Extended models add explicit industry controls (δ_j).

F.5 Estimation Notes

All OLS models use heteroskedasticity-robust standard errors. Missing values are handled through listwise deletion; sample sizes vary across models depending on data availability. Country fixed effects (γ_c) include indicators for the United States, United Kingdom, Germany, France, and Canada, with other countries as the reference category. Industry fixed effects (δ_j), where included, cover Artificial Intelligence, Biotechnology, Financial Services, Commerce & Shopping, and other major sectors.