

Funding the Future: Capital Access and Survival in Clean Technology Startups

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ABSTRACT

This paper examines the extent to which access to capital affects the survival of clean technology startups relative to conventional firms. Using a Crunchbase-derived dataset of 4,757 startups with confirmed binary outcomes, we estimate binary logistic regression models with an interaction term between funding level and clean technology classification. Clean technology startups (n=115) exhibit a raw survival rate of 40.9% compared to 62.5% for conventional firms, a gap of 21.6 percentage points, despite raising nearly three times the median capital (\$13.0M versus \$4.8M). A one-unit increase in log total funding raises the odds of survival by 48% (OR = 1.478, $p < 0.001$), and each additional funding round raises odds by 10% (OR = 1.099, $p = 0.004$). The interaction term between clean technology status and log funding is negative but statistically insignificant (coefficient = -0.071, $p = 0.639$), indicating that the marginal return to capital on survival probability is statistically indistinguishable between clean technology and conventional startups. The survival penalty for clean technology firms operates primarily through a lower baseline intercept, consistent with higher fixed capital requirements and longer pre-revenue periods characteristic of physical-technology ventures.

Keywords: clean technology, startup survival, venture capital, capital constraints, green entrepreneurship, logistic regression

Research Question: To what extent do capital market frictions constrain the survival of clean technology startups relative to comparable conventional ventures?

INTRODUCTION

The transition to a low-carbon economy depends critically on the formation and growth of clean technology ventures. These firms develop and commercialize innovations in renewable energy, energy efficiency, sustainable materials, and pollution abatement. Yet evidence suggests that

clean technology startups face numerous challenges in accessing the capital needed to survive the early stages of development, a phenomenon often described as the "valley of death" in clean energy finance (Ghosh & Nanda, 2010).

This paper investigates a specific empirical question: to what extent do capital market frictions constrain the survival of clean technology startups relative to comparable conventional ventures? Using a dataset of 4,757 startups drawn from Crunchbase, we document a large and persistent survival gap: clean technology firms survive (are acquired) at a rate of 40.9%, compared to 62.5% for non-clean-technology firms, despite raising substantially more capital on average.

We estimate logistic regression models to decompose this gap into an intercept effect (baseline survival disadvantage) and a slope effect (differential marginal return to capital). The interaction term between clean technology status and log funding is statistically insignificant, suggesting that the survival penalty operates through the baseline rather than through a differential return to capital. This is consistent with structural explanations: clean technology ventures face higher fixed capital costs, longer pre-revenue periods, and asset-intensive business models that require greater capital simply to reach equivalent survival thresholds.

The remainder of this paper proceeds as follows. Section 2 reviews the relevant literature. Section 3 describes the data and methodology. Section 4 presents empirical results. Section 5 discusses mechanisms and policy implications. Section 6 concludes.

LITERATURE REVIEW

Capital Constraints and Startup Survival

The relationship between capital access and entrepreneurial survival is well established. Evans and Jovanovic (1989) formalized the role of liquidity constraints in an occupational choice model, showing that capital constraints prevent agents with positive expected-value projects from entering entrepreneurship, generating allocative inefficiency. Building on this framework, a substantial empirical literature has confirmed that undercapitalization at founding is among the strongest predictors of early closure (Headd, 2003).

Kerr and Nanda (2015) provide quasi-experimental evidence using exogenous variation in local credit supply from US banking deregulation, finding that expansions in credit access causally raise new business formation and survival. The staging of capital also carries information content beyond its quantity: Gompers (1995) demonstrated that sequential funding rounds allow investors to resolve information asymmetries and discipline founders, making the number of rounds a signal of venture quality independent of total capital raised.

Clean Technology and Capital Constraints

Clean technology ventures differ from conventional startups in ways that may amplify capital constraints. The OECD (2021) identifies a "double externality" problem: green firms generate positive environmental externalities that are not captured in private revenues, while simultaneously bearing higher upfront costs due to the capital intensity of physical-technology deployment. The private return to clean technology entrepreneurship is therefore depressed relative to the social return.

Ghosh and Nanda (2010) document a structural asset-liability mismatch between conventional venture capital fund structures (10-year fund cycles, return expectations of 10x or more) and clean technology ventures that require longer development timelines and higher capital expenditure. This mismatch generates a financing gap at the technology readiness levels where public funding has withdrawn but private capital has not yet entered.

More recent evidence suggests that the composition of investor syndicates matters for outcomes. Shuwaikh, Tanguy, Dubocage, and Alolah (2024) find that independent venture capital (IVC)-backed clean technology firms achieve superior ESG ratings and financial performance compared to corporate VC (CVC)-backed firms, suggesting that investor type transmits non-financial capital alongside monetary investment.

Acemoglu, Aghion, Bursztyn, and Hemous (2012) provide the growth-theoretic foundation for why directed financing matters. Using an endogenous growth model with directed technical change, they show that the economy can transition to a clean technology path while maintaining output growth, but only if innovation incentives are appropriately directed toward green sectors. Without adequate capital allocation to green innovators, the market equilibrium can lock into a dirty technology path even when clean alternatives exist.

DATA AND METHODOLOGY

Data

Our data are drawn from Crunchbase, a publicly available platform tracking startup funding histories and outcomes globally. We restrict the sample to startups with confirmed binary exit outcomes, acquired or closed, yielding 4,757 observations. Startups that remain privately operating are excluded because their eventual outcomes are unknown, which would introduce ambiguity into the dependent variable.

Clean technology classification is based on Crunchbase's market category tag "Clean Technology" (n = 115). This is a narrower and more defensible classification than broader keyword-based approaches, as it reflects Crunchbase's own analyst-assigned categorization.

Total funding is the cumulative reported funding in US dollars across all funding rounds. Given the well-documented right-skewed distribution of venture capital, we apply a natural logarithm transformation. The number of funding rounds is included as a separate regressor to separate the intensive margin (capital per round) from the extensive margin (rounds completed, which carry informational and governance value per Gompers, 1995).

Variable	Full sample	Clean tech	Non-clean tech
Observations	4,757	115	4,642
Survival (acquired) rate	62.0%	40.9%	62.5%
Median total funding	\$5.0M	\$13.0M	\$4.8M
Mean funding rounds	1.95	2.00	1.95
US-based	76.1%	79.1%	76.0%

Source: Compiled from Crunchbase. Clean Technology classification per Crunchbase market tag.

The descriptive statistics reveal the central empirical puzzle: clean technology startups raise nearly three times the median capital of conventional firms (\$13.0M versus \$4.8M) yet survive at a rate 21.6 percentage points lower. This is prima facie evidence of a capital efficiency gap.

Empirical Model

We estimate a binary logistic regression where the dependent variable equals 1 if a startup was acquired (our proxy for survival) and 0 if it was recorded as closed. The baseline specification is:

$$P(\text{Survival}_i = 1) = \text{Lambda}(\beta_0 + \beta_1 * \ln(\text{Funding}_i) + \beta_2 * \text{Rounds}_i + \beta_3 * \text{US}_i + \beta_4 * \text{Year}_i + \epsilon_i)$$

We extend this to the primary specification by adding a clean technology indicator and its interaction with log funding:

$$P(\text{Survival}_i = 1) = \text{Lambda}(\beta_0 + \beta_1 * \ln(\text{Funding}_i) + \beta_2 * \text{Rounds}_i + \beta_3 * \text{US}_i + \beta_4 * \text{Year}_i + \beta_5 * \text{CleanTech}_i + \beta_6 * (\text{CleanTech} * \ln(\text{Funding}))_i + \epsilon_i)$$

The interaction term beta₆ tests whether the marginal return to capital on survival probability differs between clean technology and conventional ventures. An insignificant coefficient would indicate that the survival gap operates through the intercept alone.

We note that our survival measure acquisition versus closure excludes firms remaining privately held and operational. This introduces a potential upward bias in estimated funding effects if capital raises correlate with acquisition probability independent of operational survival. All standard errors are heteroskedasticity-robust.

RESULTS

Baseline Findings

PANEL A — BASELINE MODEL

Variable	Coefficient	Odds ratio	p-value
Log total funding	+0.391	1.478	< 0.001***
Number of funding rounds	+0.095	1.099	0.004***
US-based (dummy)	+0.500	1.649	< 0.001***
Founded year (normalized)	-0.199	0.820	< 0.001***
Intercept	-5.869	0.003	< 0.001***
Pseudo R-squared			0.155

PANEL B — FULL MODEL WITH CLEAN TECHNOLOGY INTERACTION

Variable	Coefficient	Odds ratio	p-value
Log total funding	+0.391	1.479	< 0.001***
Number of funding rounds	+0.096	1.101	0.004***
US-based (dummy)	+0.491	1.634	< 0.001***
Founded year (normalized)	-0.196	0.822	< 0.001***
Clean technology (dummy)	-0.573	0.564	0.440
CleanTech × log funding	-0.071	0.932	0.639
Intercept	-5.659	0.003	< 0.001***
Pseudo R-squared			0.164

Observations: 4,757. Standard errors are heteroskedasticity-robust.
 p < 0.01, p < 0.05, p < 0.10.

The baseline model confirms a large, precisely estimated effect of capital on survival. A one-unit increase in log total funding approximately a 2.7-fold increase in capital raises, which raises the odds of survival by 48%. Each additional funding round raises the odds by 10%, consistent with Gompers (1995) on the signaling and governance value of staged financing.

In the full model, the clean technology indicator is negative (-0.573) but not statistically significant ($p = 0.440$), and the interaction term is also indistinguishable from zero (coefficient = -0.071, $p = 0.639$). We cannot reject the hypothesis that the marginal return to capital on survival probability is the same for clean technology and conventional startups. This is an important negative finding: the survival disadvantage faced by clean technology firms does not appear to stem from a lower return on each dollar of capital raised.

Survival by Funding Distribution

Table 3 examines the non-parametric relationship between funding level and survival.

Survival rate by funding quintile, showing N, survival rate, and median funding for each quintile

Funding quintile	N	Survival rate	Median funding
Q1 (lowest 20%)	951	38.2%	\$150,000
Q2	951	55.3%	\$1,500,000
Q3	952	68.3%	\$5,000,000
Q4	951	76.7%	\$14,000,000
Q5 (highest 20%)	952	80.9%	\$54,000,000

Source: Compiled from Crunchbase.

The relationship is monotonic and increasing, with diminishing marginal returns. The largest discrete gain occurs between Q1 and Q2 (+17.1 percentage points), while the gain between Q4 and Q5 is the smallest (+4.2 percentage points). This pattern is consistent with capital constraints binding most severely at the lower tail of the funding distribution.

Table 4 presents the survival-by-rounds decomposition, consistent with Gompers's (1995) staged financing hypothesis.

Funding Rounds	N	Survival Rate
1	2,427	50.0%
2	1,196	68.1%
3	588	81.1%

4-5	409	80.7%
6-10	135	82.2%

Source: Compiled from Crunchbase.

The marginal survival gain from the first to the second funding round (+18.1 percentage points) is the largest, consistent with the first follow-on round resolving the most severe information asymmetries.

The Clean Technology Survival Gap

Table 5 summarizes the raw survival differential.

Startup Type	N	Survival Rate
Non-Clean Technology	4,642	62.5%
Clean Technology	115	40.9%

Source: Compiled from Crunchbase.

The 21.6 percentage-point gap coexists with a median funding premium of roughly 2.7 times in favor of clean technology ventures (\$13.0M versus \$4.8M). This combination constitutes direct evidence of a capital efficiency gap: clean technology startups generate lower survival probability per dollar of capital raised than conventional peers.

Table 6 presents predicted survival probabilities from the full model.

Total Funding	Non-Clean Tech	Clean Tech	Gap
\$1M	52.6%	21.9%	+30.7 pp
\$5M	68.4%	32.3%	+36.1 pp
\$10M	74.3%	37.4%	+36.8 pp
\$25M	80.8%	44.7%	+36.1 pp
\$50M	84.9%	50.4%	+34.5 pp
\$100M	88.2%	56.1%	+32.1 pp

Predicted probabilities from full logistic model (Table 2, Panel B), other covariates held at sample means.

At \$10M in total funding, a conventional startup has a predicted survival probability of 74.3%; a clean technology startup with identical capital has 37.4%, a gap of 36.8 percentage points. The gap is relatively stable across funding levels, confirming that the interaction term is near zero and the survival penalty operates through the intercept.

DISCUSSION

Economic Mechanisms

Three mechanisms likely contribute to the clean technology survival gap.

First, capital intensity and extended development timelines. Clean technology ventures in physical sectors require higher fixed capital expenditure and longer pre-revenue periods than software or services firms. In a discounted cash flow framework, a longer time to positive free cash flow reduces the present value for any given discount rate. Our finding that clean technology startups raise roughly three times the median capital yet survive at lower rates is consistent with additional capital being absorbed by higher fixed costs rather than generating proportional survival gains (OECD, 2021).

Second, investor composition and syndicate structure. Shuwaikh et al. (2024) find that venture capital investor type affects outcomes for sustainable ventures: IVC-backed firms outperform CVC-backed firms on both financial and environmental metrics. If clean technology startups are disproportionately dependent on a single type of investor or lack strategic co-investors who provide non-monetary capital, aggregate funding volume alone may fail to close the survival gap.

Third, risk perception and valuation discounting. Conventional venture capital funds operating on 10-year horizons with high return expectations may apply discount rates to clean technology ventures that do not fully account for policy tailwinds, improving cost curves, or the social option value of clean technology deployment. This mechanism cannot be directly tested with our data and remains a candidate explanation for future research.

Limitations

Several limitations warrant caution. Our survival measure captures acquisition or closure and excludes firms that remain privately operated. If acquisition probability correlates with fundraising success independently of operational survival, our estimates may overstate the causal effect of capital. The clean technology classification relies on a single Crunchbase market tag, which may misclassify firms at the boundary of sustainability. Most importantly, the cross-sectional structure of the data prevents causal identification: startups that raise more capital may be of systematically higher quality on unobserved dimensions, meaning our funding coefficients capture selection effects alongside genuine financing impacts. Instrumental variable approaches exploiting exogenous variation in local credit supply or VC fund vintage effects would provide stronger identification in future work.

Policy Implications

If the survival gap reflects structural cost disadvantages rather than differential capital efficiency, two policy implications follow. First, public capital instruments, first-loss guarantees, concessional loans, and public co-investment vehicles can reduce the effective cost of capital for clean technology ventures without requiring that the private market change its return expectations. Second, the quintile analysis shows that the marginal survival gain per dollar of capital is highest at the bottom of the funding distribution, suggesting that public interventions should target early-stage capital gaps rather than later-stage growth financing.

CONCLUSION

This paper documents a large and persistent survival gap between clean technology and conventional startups. Clean technology firms in our sample raise substantially more capital yet survive at a rate 21.6 percentage points lower than their conventional peers. The marginal return to capital on survival probability is statistically indistinguishable between the two groups: the penalty operates through the baseline, consistent with structural explanations including higher fixed costs, longer development timelines, and investor composition effects.

These findings suggest that improving clean technology startup survival does not require fundamentally different capital allocation mechanisms; rather, these ventures need to reach a higher capitalization threshold to achieve the same survival probability as conventional firms. Public policy interventions that reduce the effective cost of early-stage capital for clean technology ventures may help close this gap. Further research using quasi-experimental variation in access to capital would strengthen the causal evidence base for such interventions.

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