

Investor Transition Histories and the Timing of Follow-on Investor Entry in Early-Stage Healthcare Ventures

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Research Article

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Abstract

This study examines whether the relevance of investors' past financing experience changes as early-stage ventures attract new investors. Among 744 healthcare ventures entering private financing in 2011–2024, initial investors' completed early-to-later financing transitions in ventures with overlapping recorded categories are distinguished from transitions outside those categories. Only transitions completed before the focal financing date enter either history. A piecewise exponential model conditions on prior financing, focal-round capital and venture and investor characteristics. Category-linked history is associated with higher entry rates in months 25–36 (hazard ratio 1.549, 95% confidence interval [1.209, 1.985]) and 37–60 (1.888, [1.337, 2.666]). Direct comparisons favor category-linked history in these later intervals and outside-category history in the first year, although the first-year difference is sensitive to the multiplicity adjustment. Standardized predictions for a common cohort imply an 8.70 percentage-point difference in entry by 60 months between the upper and lower quartiles of category history; separate fixed-window regressions provide weaker evidence. The year-three association persists when broad category labels are removed and when estimation is restricted to ventures with disclosed focal capital. Differences by entry stage and biopharma status are not detected. The findings suggest that investor histories have different associations with financing at different points in venture development. Endogenous investor–venture matching prevents a causal interpretation.

1. Introduction

Early-stage ventures raise finance through successive commitments. A new investor may enter before technical evidence has developed, after a milestone, or as available cash runs low. The timing changes the information available for evaluation and the venture's dependence on its existing investors. Investor horizons also shape the financing path (Barrot, 2017). Two ventures that both secure follow-on investment can therefore face different financing conditions along the way. The study relates initial investors' histories to the timing of new-investor entry.

Prior research links investor affiliations, networks, social capital and active involvement to venture financing and development (Hsu, 2004; Hochberg et al., 2007; Bottazzi et al., 2008; Alexy et al., 2012). However, common measures of experience capture different aspects of an investor's record. Portfolio size measures investment activity, whereas a completed transition from early to later financing identifies a venture that obtained a subsequent commitment. Such cases may be relevant when another venture faces a similar financing decision. Completed transitions are distinguished from general investment activity; both can reflect the selection of promising ventures.

Recent Small Business Economics studies examine how experience and information relate to financing. Chila et al. (2025) connect founders' pre-entry experience and inherited knowledge to the time required to obtain first venture capital funding. Buchner et al. (2025) examine repeated investor-team collaboration and investment returns. Pedrazzoli et al. (2026) distinguish initial funding from subsequent financing, and Berliner (2026) relates disclosure content to investment amounts and timing. These

studies address initial access, repeated collaboration or the information disclosed during fundraising. They leave open how two types of initial-investor history compare as a venture subsequently attracts investors who were absent from its initial financing coalition.

Both histories are compared within the same ventures and duration model. The outcome is the first expansion beyond the initial investor group, and the explanatory histories distinguish completed transitions in ventures with and without category overlap. If the relative associations change over time, an average experience coefficient may conceal differences that matter for subsequent financing.

Staged-financing theory explains why this timing warrants attention. Funding intervals organize monitoring and continuation decisions (Gompers, 1995). Learning and moral hazard make new information relevant to later commitments (Bergemann & Hege, 1998), while interim evaluations affect entrepreneurial incentives (Cornelli & Yosha, 2003). Venture capitalists also report that selection and staging are central to their investment decisions (Gompers et al., 2020). Entry by a previously absent investor records an additional party's commitment within this sequence. Its conditional rate is distinguished from the cumulative entry probability and the amount raised at the focal round.

The sample contains 744 early-stage healthcare ventures whose first qualifying private financing occurred in 2011–2024. Each initial investor's history includes only transitions completed before that venture's focal financing date. Prior ventures are counted separately by whether they share a recorded category with the focal venture. The counts are log transformed, aggregated across the initial syndicate and standardized in a fixed reference cohort. The models control for prior financing, focal-round capital, venture and founder characteristics, deal structure, broader investor history, category fit, year, sector, geography and entry stage. Standard errors are clustered by the investor with the largest category-linked record in each initial syndicate.

The later direct history contrasts survive both four-test and twelve-test multiplicity adjustments; the first-year contrast passes only the former at 5%. The later category association also remains after capital adjustment, cohort restriction and accounting for documented closures. Frailty and mixture models assess specific forms of heterogeneity without excluding selection more generally. Duration predictions suggest a positive cumulative category difference, while fixed-window regressions are weaker. Stage and biopharma interactions are not detected.

The study compares category-linked and outside-category histories within the same financing process, then assesses whether focal-round capital, cohort composition and specified forms of heterogeneity account for their changing associations. This approach connects the relevance of investor experience to financing time without attributing the observed differences to investors' causal contribution.

2. Theory and research questions

2.1 Follow-on investor entry as expansion of the financing coalition

Entrepreneurial financing is a sequence of evaluations under uncertainty. Early ventures offer sparse evidence; later investors observe more development but confront questions about feasibility, execution, regulation and scale. Affiliations convey quality when underlying attributes are hard to observe (Stuart et al., 1999; Hsu, 2004), and categories make novel organizations comparable but can penalize ambiguity (Zuckerman, 1999; Navis & Glynn, 2010; Pontikes, 2012).

A new investor commits resources after making its own screening and coordination decisions. Its entry expands the financing coalition beyond the original participants. This event is not necessarily a sign of success: some strong ventures need no additional investor, some follow-on rounds reflect distress, and commercial databases omit transactions. It nevertheless distinguishes a new external commitment from reinvestment by existing investors.

Entry timing can affect the alternatives available during fundraising. An additional investor may reduce dependence on an incumbent before cash runs low, while waiting may allow a venture to negotiate on the basis of stronger evidence. The same company can be evaluated before or after technical validation, a clinical readout or regulatory clarification. Staging also places monitoring and continuation decisions at different points in development (Gompers, 1995; Cornelli & Yosha, 2003). These considerations give financing timing economic significance, although the data do not measure bargaining power, dilution, valuations or contractual tranches.

2.2 Completed financing transitions as investor experience

Venture capital research distinguishes investor network position, human capital and specialization (Sorenson & Stuart, 2001; Dimov & Shepherd, 2005; Hochberg et al., 2007; Alvarez-Garrido, 2023). Collaborative experience among syndicate partners is related to exits (Wang et al., 2022), and venture attributes and founders' prior outcomes influence investor selection and funding (Baum & Silverman, 2004; Gompers et al., 2010). A history of completed financing transitions captures a different feature: previous cases in which an early investment was followed by later-stage financing.

A completed transition is counted when an investor first enters a venture at an eligible early stage and that venture subsequently reaches one of the specified later financing states. An early investment without such a transition contributes to investment volume but not to the transition count. For focal venture i , the later financing must precede its focal date. Subsequent developments in an investor's portfolio cannot change the history assigned at that date.

A prior transition may provide a reference for what evidence was assembled and which investors participated in obtaining later finance. Research on organizational learning and experience transfer motivates this interpretation (De Clercq & Dimov, 2008; Clarysse et al., 2013). The same transition may

also reflect access to attractive ventures or established networks. The measure records the financing history without identifying which of these resources was used.

Several explanations are consistent with an association between this history and subsequent entry. Investors may select ventures already likely to attract later capital, their participation may certify a venture's quality, or they may contribute knowledge and introductions. Two-sided matching makes these explanations difficult to separate (Sørensen, 2007). Quas et al. (2021) study nonfinancial venture-capital resources using a difference-in-differences design around participative loans. The data provide no comparable counterfactual, so investor histories are interpreted as observed characteristics rather than assigned treatments.

Research Question 1. How is the initial syndicate's completed-transition history associated with the timing and accumulated probability of entry by a previously absent investor?

2.3 Why category overlap can make a prior transition more informative

Completed transitions may be more informative when prior and focal ventures share an evaluative context. Biopharmaceutical, device, diagnostic, digital-health and care-service ventures confront different combinations of technical evidence, regulation, reimbursement, adoption and unit economics, so the same financing boundary can represent different underlying work.

Recorded category overlap provides a limited measure of this shared context. A prior case may offer an analogy, connect a venture to investors familiar with the category, or reflect the initial investor's choice of a recognizable opportunity set (Gavetti et al., 2005; Grégoire et al., 2010). Overlap is measured using database labels, which need not indicate technological proximity.

The outside-category history counts transitions that meet the same timing and stage rules but have no recorded category overlap. Including it alongside category-linked history distinguishes overlap from general transition accumulation. Because labels are incomplete and knowledge can transfer across categories, overlapping histories are not assumed to be more relevant at every point in time.

Research Question 2. How does the association of category-linked transition history with entry compare with that of outside-category history over time?

2.4 Development timing and alternative explanations

Category-linked histories may become more relevant as a venture develops evidence that resembles a previously financed case. Broader histories may instead connect a venture to a wider set of financiers before that evidence is available. These possibilities imply different relative associations over time. A stable investor-quality explanation would predict a more consistent ranking. The temporal comparison can distinguish these patterns, but it cannot identify what investors learned, whom they introduced or which milestones were reached.

Larger initial rounds offer another explanation for later entry. Investors with stronger category histories may finance ventures more generously at the outset, allowing them to postpone fundraising. Focal capital may therefore lie between investor selection and subsequent entry. Conditioning on it compares ventures with similar recorded initial financing, but does not identify the total effect of investor history. Burn rates, remaining cash and intermediate financing are unobserved.

The ventures still at risk also change over time. Later hazards are estimated among those that have not yet attracted a new investor. If unobserved entry propensity differs across ventures, selective exit from the risk set can produce a changing marginal association even when individual-level effects remain constant (Vaupel & Yashin, 1985). The analysis uses gamma frailty and a mixture model that allows some ventures never to attract entry. These models assess specific selection processes rather than eliminate unobserved heterogeneity as an explanation.

Research Question 3. Does the category/outside-history comparison vary over elapsed time, and how much of the observed pattern remains after conditioning on focal capital, common cohort support and unobserved heterogeneity?

Additional analyses compare the histories' temporal associations for seed/pre-seed versus Series A/B entrants and for biopharma versus other healthcare ventures. Stage and sector indicate broad differences in development context, but do not identify dated milestones. Each model includes group-specific baseline hazards and all history-by-interval interactions. Joint tests assess whether the profiles differ between groups.

3. Data and measurement

3.1 Data sources and sample

The analysis combines licensed PitchBook and Crunchbase financing records with founder information and ClinicalTrials.gov histories. Company records were linked using current, previous and legal names, followed by checks of descriptions, headquarters and websites where needed. The linked sources provide financing dates, stages, investors, disclosed amounts, categories, locations and recorded outcomes. ClinicalTrials.gov supplies an indicator of whether an interventional trial began before focal financing. Categories are observed in the database snapshot. Financing dates refer to recorded transactions; they do not establish cash-settlement dates or when the information became publicly available. Pre-focal eligibility therefore follows recorded event dates rather than reconstructing the information available to investors at the time. Source linkage and reconstruction are detailed in the Supplementary Information.

The focal date is the earliest qualifying private-investor entry. All investors recorded on that date form the initial syndicate. Eligible focal events are pre-seed, seed, angel, convertible note, crowdfunding, Series A, Series B or equivalent early-stage records; debt, grants, private equity and later-stage first observations are excluded. The resulting cohort contains 744 ventures financed in 2011–2024, all of

which enter the primary model. Entry-year indicators distinguish 2011–2022 and a pooled 2023–2024 category. Table 1 reports cohort composition.

Complete-window samples decline from 739 ventures at 12 months to 576 at 60 months. The duration model uses all observed follow-up and records 454 first entries, so its event total differs from the fixed-horizon counts.

Table 1
Sample, outcomes, and exposure distributions

Panel / measure	N or events	Mean / share	SD	Median	Range
A. Cohort and event timing					
Eligible early-stage ventures	744	—	—	—	2011–2024 focal years
Ventures in primary duration model	744	—	—	—	527 carrier clusters
New investor by 12 months	147 / 739	19.9%	—	—	complete-window sample
New investor by 24 months	299 / 719	41.6%	—	—	complete-window sample
New investor by 36 months	396 / 690	57.4%	—	—	complete-window sample
New investor by 60 months	390 / 576	67.7%	—	—	complete-window sample
First-entry events in duration panel	454	—	—	—	8,258 intervals
B. Focal entry and sector					
Seed/pre-seed entry	451	60.6%	—	—	—
Series A entry	250	33.6%	—	—	—
Series B entry	43	5.8%	—	—	—
Biopharma	411	55.2%	—	—	—
Digital health	120	16.1%	—	—	—
Device/diagnostics	114	15.3%	—	—	—
Care services	93	12.5%	—	—	—
Other health	6	0.8%	—	—	—
C. Exposure and covariate summaries					
Category-overlapping record, log raw	744	0.841	1.160	0	0–4.489
Notes: Descriptives use all 744 ventures. The category-overlapping and outside-category variables are log(1 + count) measures standardized in the fixed 690-venture reference cohort. Focal capital is separate from strictly pre-focal capital. Founder-team fields may be incomplete; additional measurement diagnostics are reported in the supplement.					

Panel / measure	N or events	Mean / share	SD	Median	Range
Category-overlapping transition count	744	4.565	9.869	0	0–88
Outside-category record, log raw	744	0.970	1.352	0	0–5.170
Initial syndicate size	744	1.886	1.567	1	1–13
Founder-team size	744	1.755	0.945	1	1–6
Venture age at focal entry, years	744	2.047	1.863	2	-1–10
Prior financing rounds	744	0.519	1.059	0	0–8
Focal capital disclosed, USD million	513 / 744	14.489	30.816	3.500	0.015–411.770
Notes: Descriptives use all 744 ventures. The category-overlapping and outside-category variables are $\log(1 + \text{count})$ measures standardized in the fixed 690-venture reference cohort. Focal capital is separate from strictly pre-focal capital. Founder-team fields may be incomplete; additional measurement diagnostics are reported in the supplement.					

3.2 Focal event and outcome

The outcome is the first post-focal appearance of an investor absent from the initial syndicate, identified by stable IDs where available. Reinvestment only by original members is not an event. Follow-up ends at new-investor entry, the five-year limit of 1,826 days, or the administrative endpoint of 3 June 2024, whichever comes first.

The panel contains 8,258 intervals and 727,659 observed venture-days across 744 ventures. Quarters are defined as 365.25/4 days, with the final interval shortened to the observed event or censoring date. Partial intervals contribute their observed exposure, including events on the inclusive 1,826-day boundary. Separate fixed-window indicators require complete follow-up at 12, 24, 36 and 60 months. The competing-risk analysis represents documented closure as a separate event.

3.3 Category-linked transition history

For every investor j entering focal venture i on date t_i , prior portfolio ventures must satisfy four conditions:

1. investor j 's first recorded entry into the prior venture was at a qualifying seed or early stage;
2. that prior venture subsequently reached Series C or later, private equity, secondary market, or a post-IPO financing state;
3. the later financing state occurred strictly before t_i ; and
4. the prior venture is not focal venture i .

Transitions completed after t_i contribute nothing, preventing later portfolio outcomes from changing an earlier exposure. This temporal restriction applies to entry and financing-transition dates. The database categories used to link prior and focal ventures are snapshot labels rather than historical classifications dated at t_i .

Each eligible transition is classified by whether the prior and focal ventures share a recorded company category. The count is then transformed as $\log(1 + \text{count})$. The primary syndicate measure takes the largest transformed count among its initial investors. It represents the strongest observed overlapping history within the group, without assuming that this investor acted on the venture's behalf.

The venture-level measure is standardized in the fixed 690-firm complete-36-month reference cohort and held fixed across analyses; its SD is 1.006 in all 744 ventures. In the full sample, the unstandardized log-count averages 0.841 (SD 1.160). The raw count averages 4.56, reaches 88 and equals zero for 415 ventures.

The outside-category record applies identical timing and stage rules to eligible transitions without recorded overlap. In the full sample, its log-count averages 0.970 (SD 1.352) and equals zero for 401 ventures. Both records enter together, which reduces the possibility that the focal measure only captures a large transition portfolio.

3.4 Sensitivity to broad category labels

Both histories are recalculated after excluding four broad labels: Health Care, Healthcare, Life Science and Medical. Fourteen ventures then have no remaining category, and zero category-linked counts increase from 415 to 463. This analysis tests whether the association depends on overlap through broad labels.

3.5 Control variables

Pre-focal capital is the sum of disclosed financing amounts strictly before the focal date. Focal capital is entered separately and sums disclosed USD amounts across deduplicated round IDs on that date. Amounts are available for 513 of 744 ventures, with a median of \$3.50 million. The term $\log(1 + \text{focal USD})$ is standardized among disclosed amounts. Missing amounts receive zero on this centered scale and a separate missingness indicator; they are not treated as zero funding. Other controls include founder-team size and the presence of a female founder; venture age, prior financing rounds and trial initiation; investor portfolio size and missing history; category fit; syndicate size, entry stage, year, sector and geography. Category fit and sector use snapshot information. Age is measured as focal year minus founding year; the supplement describes the one negative-age observation.

4. Empirical strategy

4.1 Piecewise exponential models

The primary specification is a piecewise exponential model. For venture i in quarter q , E_{iq} is observed exposure in quarter units and μ_{iq} is integrated event intensity. The model can be estimated using a Poisson likelihood with log exposure as an offset (Holford, 1980; Laird & Olivier, 1981):

$$\log \mu_{iq} = \log E_{iq} + \alpha_q + \sum_{k=1}^4 \beta_k C_i I(q \in k) + \sum_{k=1}^4 \delta_k O_i I(q \in k) + Z_i' \theta$$

C_i and O_i are the standardized category-linked and outside-category log counts. The baseline α_q varies by quarter, while history coefficients vary across months 1–12, 13–24, 25–36 and 37–60. Z_i contains focal capital, its missingness indicator and controls. Administrative censoring is assumed independent conditional on these variables. Joint tests assess whether category coefficients are zero or equal across intervals. The β_k – δ_k contrasts compare one reference standard deviation of each history, rather than equal raw counts.

For comparison, a proportional specification imposes one slope for each history throughout follow-up:

$$\log \mu_{iq} = \log E_{iq} + \alpha_q + \beta C_i + \delta O_i + Z_i' \theta$$

A common slope summarizes the conditional rate association across follow-up and is assessed alongside the test of equality across intervals. Because focal capital may partly mediate investor selection or affiliation, neither specification estimates the total causal effect of investor history.

Standard errors are clustered by the investor with the largest initial category-linked record, giving 527 clusters. Tests use a finite-sample correction and t/F reference distributions with 526 degrees of freedom; the supplement specifies the calculation. Because the carrier can be arbitrary when histories tie at zero, alternative estimates cluster by venture. Tests are two-sided. Supplementary Table S7 reports all primary-model coefficients.

4.2 Secondary fixed-window models

Linear-probability models estimate associations with new-investor entry by 12, 24, 36 and 60 months. Both histories enter together with focal capital and the other controls. The coefficients measure probability-point differences per reference-cohort standard deviation. As in the duration models, they remain conditional associations because deal structure can reflect investor–venture matching.

The regressions use horizon-specific complete-window samples with fixed exposure scaling. They describe entry by a given horizon rather than the conditional rate within an interval.

4.3 Multiple testing

Inference uses two-sided p-values and Benjamini–Hochberg q-values, with .05 as the principal threshold (Benjamini & Hochberg, 1995). Results meeting only .10 are identified separately. Duration families contain four intervals per history or direct contrast; the primary results also adjust all twelve tests jointly.

The two-part family contains sixteen component-by-interval tests, and fixed-window families contain four horizons.

The study was not preregistered. Complete temporal profiles are exploratory, with fixed-window models secondary. Sensitivity estimates and null results appear in the Supplementary Information.

4.4 Selection and sensitivity analyses

Initial-financing explanations are assessed by relating category history to focal capital and amount disclosure, allowing capital coefficients to vary by interval, and restricting estimation to disclosed amounts. Other checks remove broad category labels or estimate within-investor fixed effects. Omitted-variable sensitivity for the 36-month linear-probability coefficient follows Cinelli and Hazlett (2020), conditioning on all other regressors.

A two-part specification separates zero history from intensity among positive records. For each history, an indicator for a positive record and a centered positive log count interact with the four intervals. Both histories, focal capital and controls enter together. Centering and scaling use the reference cohort. The category indicator compares a reference of approximately 5.61 cases with zero history; its intensity measure has a log-count standard deviation of 1.0079. It is not a zero-to-one-case comparison.

Gamma frailty models allow unobserved heterogeneity at venture or carrier-investor level. Variance is estimated freely and fixed at values from 0.25 to 4 in separate specifications. Under a common gamma distribution independent of covariates, a constant conditional hazard ratio cannot produce a marginal ratio that crosses one (Lancaster, 1979; Vaupel & Yashin, 1985). This property does not extend to all mixing distributions, and identification depends on the model assumptions (Elbers & Ridder, 1982). A mixture model separately allows ventures never to attract entry, fixing susceptibility at the covariate origin to 90%, 80% or 70%. The supplementary methods give the equations, estimation details and identification limits.

Fine–Gray models treat documented closure as a competing event (Fine & Gray, 1999). Financing takes precedence when it occurs before or on the same day as closure. Incomplete closure dates are bracketed using earliest and latest possible dates; 36 undated failure flags are excluded in a separate check. Both proportional and four-interval specifications are estimated. Inference uses 399 carrier-cluster bootstrap draws that re-estimate censoring weights and coefficients. Subdistribution hazard ratios concern cumulative incidence and differ from the primary hazard ratios.

4.5 Cumulative probabilities and contextual differences

Predicted entry probabilities are standardized to 576 ventures with complete 60-month observation. Each history is set to its 25th or 75th percentile while other variables remain at observed values. Quarterly rates are integrated and probabilities averaged across ventures. The contrasts span 1.203 reference standard deviations for category history and 1.242 for outside history. Pointwise 95% intervals

use the carrier-cluster covariance and delta method. These are predictions under the primary censoring convention, not Fine–Gray cumulative incidences or causal effects.

Stage and sector comparisons add eight history-by-interval interactions and group-specific quarterly baselines. The two joint interaction tests receive a two-test Benjamini–Hochberg adjustment. The supplement details these models and the probability calculations.

5. Results

5.1 Primary flexible duration evidence

Category-history hazard ratios are 0.815 in months 1–12 and 1.000 in months 13–24, neither significant. They rise to 1.549 (95% CI [1.209, 1.985]) in months 25–36 and 1.888 ([1.337, 2.666]) in months 37–60. Both later estimates have $q = .0011$ within the four-interval family (Table 2).

Table 2
Exact-exposure flexible hazard of first new-investor entry

Window / history	HR [95% CI]	p	q(4)	q(12)
1–12 months · Category	0.815 [0.635, 1.046]	0.1078	0.1438	0.1844
13–24 months · Category	1.000 [0.807, 1.240]	0.9974	0.9974	0.9974
25–36 months · Category	1.549 [1.209, 1.985]	0.000561	0.0011	0.0034
37–60 months · Category	1.888 [1.337, 2.666]	0.000323	0.0011	0.0034
1–12 months · Outside	1.338 [1.035, 1.730]	0.0261	0.1043	0.0522
13–24 months · Outside	1.199 [0.952, 1.510]	0.1229	0.1926	0.1844
25–36 months · Outside	0.867 [0.676, 1.112]	0.2618	0.2618	0.3142
37–60 months · Outside	0.732 [0.481, 1.114]	0.1445	0.1926	0.1926
1–12 months · Category / outside	0.609 [0.398, 0.933]	0.0228	0.0304	0.0522
13–24 months · Category / outside	0.834 [0.571, 1.220]	0.3497	0.3497	0.3815
25–36 months · Category / outside	1.786 [1.186, 2.689]	0.0055	0.0144	0.0216
37–60 months · Category / outside	2.581 [1.294, 5.150]	0.0072	0.0144	0.0216
Notes: N = 744 ventures, 8,258 intervals, 454 events and 527 carrier clusters. Focal capital and its missingness indicator are included; entry years 2023–2024 are pooled. q(4) adjusts four intervals per history or contrast; q(12) adjusts all twelve tests. Direct contrasts compare one reference standard deviation of each history.				

Category slopes are jointly nonzero, $F(4,526) = 7.565$, $p = .000006$, and equality across intervals is rejected, $F(3,526) = 8.607$, $p = .000014$. The estimates indicate temporal variation in the conditional association. They do not identify an exact 24-month threshold, since each later interval includes only ventures that remain without a new-investor event.

Outside-category hazard ratios are 1.338, 1.199, 0.867 and 0.732 across the four intervals. None passes 5% or 10% FDR within its four-interval family; the first-year coefficient has $p = .0261$ and $q = .1043$. The joint-zero and equality tests give $p = .0168$ and $.0111$. Differences between histories are assessed using direct contrasts rather than their separate significance levels.

Direct category/outside hazard-ratio contrasts are 0.609, 0.834, 1.786 and 2.581 across the four intervals (Table 2). The first-year contrast favors outside-category history; the two later contrasts favor category-linked history. Their respective q-values are .0304, .0144 and .0144 under the four-test adjustment. With all twelve tests combined, the first-year q-value rises to .0522, while both later q-values are .0216. The later differences therefore meet the 5% threshold under either adjustment; the first-year result is sensitive to the choice of family.

Later intervals include fewer ventures and older cohorts (Table 3). Months 25–36 contain 420 at-risk ventures and 102 events; months 37–60 contain 294 ventures and 50 events, with no 2022–2024 entrants. Restricting the sample to the 617 ventures entering in 2011–2019 retains later category hazard ratios of 1.564 [1.209, 2.023] and 1.836 [1.305, 2.584], both $q = .0014$. The first-year direct contrast is 0.599 ($q = .0315$). This restriction addresses changing cohort composition but not selection into later risk sets. Supplementary Table S1 reports alternative clustering and year indicators.

Table 3

Cohort composition of the risk sets and common-cohort estimates Panel A. Ventures contributing positive exposure in each interval

Months	At risk	Events	2011–15	2016–19	2020–21	2022–24
1–12	744	147	208	409	89	38
13–24	592	155	163	321	77	31
25–36	420	102	112	236	60	12
37–60	294	50	78	173	43	0
Notes: Entry-year groups count distinct ventures within an interval, not venture-quarter rows. Counts sum to the displayed at-risk N. Events sum to 454 across intervals.						
Panel B. Entry restricted to 2011–2019; full-sample scaling retained						

Months	Category HR [95% CI]	q(4)	Category / outside [95% CI]	q(4)
1–12	0.805 [0.619, 1.045]	0.1374	0.599 [0.384, 0.933]	0.0315
13–24	1.098 [0.886, 1.362]	0.3913	0.969 [0.665, 1.413]	0.8710
25–36	1.564 [1.209, 2.023]	0.0014	1.710 [1.116, 2.620]	0.0315
37–60	1.836 [1.305, 2.584]	0.0014	2.341 [1.168, 4.689]	0.0315
Notes: N = 617 ventures, 415 events and 444 carrier clusters. Primary scaling and controls are retained; year indicators are rebuilt. Four-interval adjustments are separate for histories and contrasts.				

5.2 Proportional summaries and documented competing risks

Proportional hazard ratios are 1.094 for category history ($p = .2422$) and 1.112 for outside history ($p = .2165$), with a direct ratio of 0.984 ($p = .8946$; Table 4). These nonsignificant constant-slope estimates do not establish equal cumulative entry probabilities.

Table 4
Documented-closure sensitivity and proportional summaries

Model / history / interval	Effect [95% CI]	p	q(4)
Fine-Gray category · 1–12	0.816 [0.635, 1.049]	0.1129	0.1505
Fine-Gray category · 13–24	1.002 [0.784, 1.282]	0.9854	0.9854
Fine-Gray category · 25–36	1.536 [1.152, 2.048]	0.0036	0.0142
Fine-Gray category · 37–60	1.882 [1.186, 2.985]	0.0074	0.0147
Proportional PEM · Category	1.094 [0.941, 1.272]	0.2422	—
Proportional PEM · Outside	1.112 [0.939, 1.316]	0.2165	—
Proportional PEM · Category / outside	0.984 [0.773, 1.252]	0.8946	—
Proportional Fine-Gray · Category	1.093 [0.925, 1.293]	0.2946	—
Notes: Fine-Gray estimates are subdistribution hazard ratios; piecewise exponential estimates are hazard ratios. Fine-Gray uses 744 ventures, 454 financing events and seven documented competing closures at the earliest-date bound, versus six at the latest bound. Inference uses 399 carrier-cluster bootstrap draws. q(4) applies to flexible category slopes; proportional tests are unadjusted.			

The flexible Fine-Gray category subdistribution hazard ratios are 1.536 and 1.882 in the two later intervals; both pass 5% FDR. The proportional estimate is 1.093 ($p = .2946$). All 36 proportional coefficients agree with R's `cmprsk` implementation within 1.1×10^{-8} . The small number of documented closures does not account for the later association, but limits conclusions about mortality more broadly. Supplementary Table S2 reports closure-date and undated-flag sensitivities.

5.3 Fixed-window probability estimates

The 36-month category coefficient is 5.60 percentage points (95% CI $[-0.88, 12.08]$, $p = .0900$, $q = .1800$), meeting only the unadjusted 10% threshold. The category/outside difference is 5.01 points ($p = .3203$). Endpoint evidence is weaker than the year-three hazard association.

Category coefficients at 12, 24 and 60 months are -3.26 , 0.59 and 5.04 percentage points (Table 5). None meets the adjusted 10% threshold. These results also provide weaker endpoint evidence than the standardized duration predictions below. Supplementary Table S3 reports ancillary investor-type and recorded exit outcomes.

Table 5
Secondary fixed-window category-record estimates

Horizon	N	Events	Estimate, pp [95% CI]	p	q(4)
12 months	739	147	-3.26 [-8.85, 2.32]	0.2512	0.3349
24 months	719	299	0.59 [-6.08, 7.26]	0.8627	0.8627
36 months	690	396	5.60 [-0.88, 12.08]	0.0900	0.1800
60 months	576	390	5.04 [-0.20, 10.28]	0.0593	0.1800
Notes: Each focal-capital-adjusted coefficient is per reference-cohort SD, with carrier-clustered inference. q adjusts four horizons within the category-history family. None passes .05 or .10 FDR. Complete-window denominators differ across horizons.					

5.4 Initial capital and category definitions

Among disclosed rounds, one standard deviation of category history is associated with 0.392 log points more focal capital ($p = .0000105$), approximately 48%. Its association with amount disclosure is not significant ($p = .3976$). Allowing interval-specific capital coefficients retains later category hazard ratios of 1.442 and 1.905, both passing 5% FDR. Restricting to disclosed amounts retains the year-three association (HR 1.560, $q = .00596$) but not months 37–60 (HR 1.683, $q = .1992$; Table 6).

Table 6
Focal-capital and category-representation sensitivities

Specification	Interval	HR [95% CI]	p	q(4)
Without focal capital	1–12	0.868 [0.680, 1.107]	0.2539	0.3386
Without focal capital	13–24	1.064 [0.861, 1.314]	0.5670	0.5670
Without focal capital	25–36	1.631 [1.260, 2.111]	0.000217	0.000866
Without focal capital	37–60	1.860 [1.308, 2.645]	0.000581	0.0012
Interval-specific capital	1–12	0.912 [0.710, 1.172]	0.4721	0.6295
Interval-specific capital	13–24	1.006 [0.787, 1.286]	0.9608	0.9608
Interval-specific capital	25–36	1.442 [1.113, 1.869]	0.0057	0.0115
Interval-specific capital	37–60	1.905 [1.303, 2.785]	0.000911	0.0036
Disclosed amounts only	1–12	0.813 [0.621, 1.064]	0.1312	0.1992
Disclosed amounts only	13–24	1.060 [0.824, 1.364]	0.6488	0.6488
Disclosed amounts only	25–36	1.560 [1.187, 2.049]	0.0015	0.0060
Disclosed amounts only	37–60	1.683 [0.829, 3.419]	0.1494	0.1992
Generic labels excluded	1–12	0.916 [0.726, 1.155]	0.4560	0.6080
Generic labels excluded	13–24	0.984 [0.814, 1.188]	0.8631	0.8631
Generic labels excluded	25–36	1.446 [1.131, 1.849]	0.0033	0.0132
Generic labels excluded	37–60	1.722 [1.049, 2.825]	0.0316	0.0631

Notes: All specifications except disclosed amounts use 742 ventures and 454 events. The disclosed-amount sample has 511 ventures and 337 events. These models exclude the two 2024 entrants and use separate year indicators through 2023. Table 2 uses all 744 ventures. q(4) adjusts category slopes within each specification.

Removing broad labels retains the year-three category association (HR 1.446, $q = .01322$). The 37–60-month estimate is 1.722, meeting only the adjusted 10% threshold ($q = .06312$). Neither later direct contrast passes FDR adjustment. Thus year three is more stable than the claim of category superiority across the later intervals.

5.5 Frailty and mixture-model estimates

The freely estimated gamma variances reach the numerical zero boundary. Under imposed variances from 0.25 to 4, both later category slopes remain positive at 5% FDR, while the direct contrasts lose precision. At $\theta = 2$, their q -values are .1365 and .0613; neither later contrast passes 10% FDR at $\theta = 4$. In the mixture model, later contrasts pass 5% FDR at origin susceptibility of 90%, but neither passes 10% at 80% or 70%. The year-three category slope at 70% has $q = .0575$. The unconstrained susceptibility equation is not identified reliably. Supplementary Tables S8 and S9 give the estimates and fit statistics. These checks do not establish that unobserved selection is absent.

5.6 Positive histories and their intensity

The reference-positive category history has a year-three hazard ratio of 2.626 (95% CI [1.573, 4.385], sixteen-test $q = .003817$). Intensity among positive records is not significant in that interval (Table 7).

Table 7
Category-history presence and positive-history intensity

Category component	Interval	HR [95% CI]	p	q(4)	q(16)
Reference positive vs zero	1–12	0.645 [0.377, 1.105]	0.1101	0.1468	0.2202
Reference positive vs zero	13–24	1.071 [0.686, 1.672]	0.7616	0.7616	0.7616
Reference positive vs zero	25–36	2.626 [1.573, 4.385]	0.000239	0.000955	0.0038
Reference positive vs zero	37–60	2.583 [1.190, 5.604]	0.0165	0.0329	0.0781
Positive-history intensity	1–12	0.898 [0.699, 1.154]	0.4008	0.5345	0.5345
Positive-history intensity	13–24	0.963 [0.761, 1.219]	0.7544	0.7544	0.7616
Positive-history intensity	25–36	1.261 [0.923, 1.722]	0.1452	0.2905	0.2582
Positive-history intensity	37–60	1.945 [1.341, 2.821]	0.000477	0.0019	0.0038
Notes: Both histories' components, focal capital and all controls enter jointly (N = 744). The reference-positive category history is approximately 5.61 cases, with positive log-count SD 1.0079. q(16) adjusts both histories, both components and four intervals. Presence is not a zero-to-one-case comparison.					

In months 37–60, positive-history intensity has HR 1.945 (95% CI [1.341, 2.821], sixteen-test $q = .003817$). The reference-positive comparison meets only the adjusted 10% threshold (HR 2.583, $q = .07811$). These are separate comparisons, not effects of obtaining a first completed case.

5.7 Cumulative entry and contextual differences

The standardized category interquartile difference rises from – 4.67 percentage points at 12 months to + 8.70 at 60 months (pointwise 95% CI [2.62, 14.78]). Earlier intervals include zero. The outside-history difference rises initially, then falls to + 0.20 points at 60 months. Figure 1 and Table 8 report these model-dependent probabilities and their uncertainty.

Table 8
Common-reference cumulative probability contrasts

History	Months	Q75 – Q25, pp	Pointwise 95% CI
Category	12	-4.67	[-10.53, 1.18]
Category	24	-3.00	[-9.38, 3.38]
Category	36	4.17	[-2.63, 10.97]
Category	60	8.70	[2.62, 14.78]
Outside	12	6.58	[0.75, 12.41]
Outside	24	8.48	[1.35, 15.61]
Outside	36	3.47	[-3.46, 10.39]
Outside	60	0.20	[-6.19, 6.59]
Notes: N = 576 throughout. Quarter length is 365.25/4 days. Quartile contrasts span 1.203 reference standard deviations for category history and 1.242 for outside history. Intervals are pointwise, without simultaneous adjustment. Table 5 reports one-standard-deviation linear-probability estimates in horizon-specific cohorts.			

Joint interaction tests do not detect differences by entry stage ($p = .4812$) or biopharma status ($p = .6655$), with $q = .6655$ for both (Supplementary Table S4). Supplementary Tables S5 and S6 report subgroup estimates and risk-set counts. Nondetection does not establish equivalence between groups.

6. Discussion

6.1 Investor experience and follow-on financing

The main finding is that category-linked and outside-category histories have different relative associations over the financing process. The first-year estimate favors outside-category history, whereas later estimates favor category-linked history. Year three provides the most consistent category association across the sensitivity analyses. This pattern qualifies the use of a single experience coefficient: an investor characteristic associated with entry early in the financing process need not have the same association later.

The comparison complements recent studies with different financing outcomes. Chila et al. (2025) examine founders' experience before first venture capital funding, and Buchner et al. (2025) study repeated investor teams and returns. Berliner (2026) considers timing alongside amount in equity crowdfunding. The present study compares category-linked and outside-category investor histories as ventures attract investors absent from their initial group.

6.2 Financing timing and interpretation

Staging places new investors' evaluations at different points in venture development. Earlier entry may broaden financing alternatives when technical evidence is limited. Later entry may follow stronger evidence, but may also occur when the venture has become dependent on additional cash. The data do not establish which situation applies to a particular venture. They suggest that explanations of investor experience should consider financing needs and the information available when new investors commit.

For a common cohort, the duration model implies a positive category contrast by 60 months. Fixed-window regressions provide weaker evidence, and the proportional benchmark is not significant. The changing conditional association is therefore better supported than a model-independent increase in overall financing access.

Under the common-gamma assumptions, selective attrition cannot turn a constant conditional hazard ratio into a marginal ratio that crosses one. This property does not cover other mixing distributions, covariate-dependent heterogeneity or misspecification. Imposed gamma variance widens the direct history contrasts, and the mixture estimates depend on poorly identified susceptibility assumptions. These checks therefore do not separate the temporal pattern from all changes in risk-set composition.

Initial financing offers a plausible part of the explanation: stronger category histories are associated with larger focal rounds. Controlling for the amount, including interval-specific capital coefficients, leaves the later association in place. Recorded focal capital therefore does not fully account for the pattern. Selection, development progress and financing needs remain compatible explanations because burn rates, cash balances, terms and intermediate capital are unobserved, and focal capital may itself be a mediator.

6.3 Category overlap and evaluation context

The evidence for a shared evaluation context is limited. Removing broad labels preserves the year-three category association but weakens the later direct comparisons. The stage and biopharma interactions are not detected. Establishing the proposed explanation would require dated milestones and evidence about investor introductions, due diligence or negotiation. Database category overlap identifies a recorded relationship between ventures, without demonstrating common technology or investor capabilities.

6.4 Implications for entrepreneurs and investors

Entrepreneurs can ask potential investors how their previous portfolio companies obtained later finance, when those commitments occurred and what evidence was available. Such information may help frame discussions about development milestones and future financing needs. Investors can use the same questions when considering the fit between their experience and a venture's expected financing path. For researchers, the findings support reporting both the timing of entry and entry by a fixed horizon. None of these estimates identifies an optimal fundraising month or a preferred investor for a particular venture.

6.5 Limitations

Endogenous investor–venture matching is the central limitation. The gamma models assume a particular distribution of residual heterogeneity and its independence from observed covariates. The mixture model allows susceptibility to depend on histories, but does not identify exogenous assignment. Neither replaces a design capable of separating selection, certification and investor conduct. The .066 robustness value concerns the secondary 36-month linear-probability point estimate and provides no sensitivity bound for the interval-specific hazard ratios. The first-year direct contrast is also sensitive to whether multiplicity is adjusted within four tests or across twelve.

Commercial databases omit transactions and contain identity and stage inconsistencies. Focal amounts are missing for 231 ventures, and disclosure diagnostics cannot establish that this missingness is ignorable. Twenty ventures have a recorded closure date with day, month or year precision; 36 additional closure/failure flags have no date. Only six or seven dated closures precede the financing event or observation limit, depending on date precision, so the competing-risk findings concern documented closure and do not solve incomplete mortality ascertainment. Snapshot labels and retrospectively recorded financing dates limit claims about information available at focal entry.

The maximum-history measure does not identify which syndicate member contributed to subsequent financing. New-investor entry records expansion of the financing group; valuations, returns, dilution, clinical value and social benefits are not observed. The results concern the linked healthcare cohort and may not generalize to other sectors or to ventures missing from the commercial databases.

7. Conclusion

Initial investors' completed financing histories are associated with new-investor entry differently over time. Category-linked history has its most consistent positive association in year three, while the first-year relative comparison favors outside-category history but is sensitive to the multiplicity adjustment. The later category association remains after several financing and cohort adjustments, although direct comparisons weaken under some category and heterogeneity assumptions. These findings connect investor experience to the timing of follow-on finance. They do not identify a causal benefit from selecting investors with a particular history.

Declarations

Author Contribution

The author did it all by herself.

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Figures

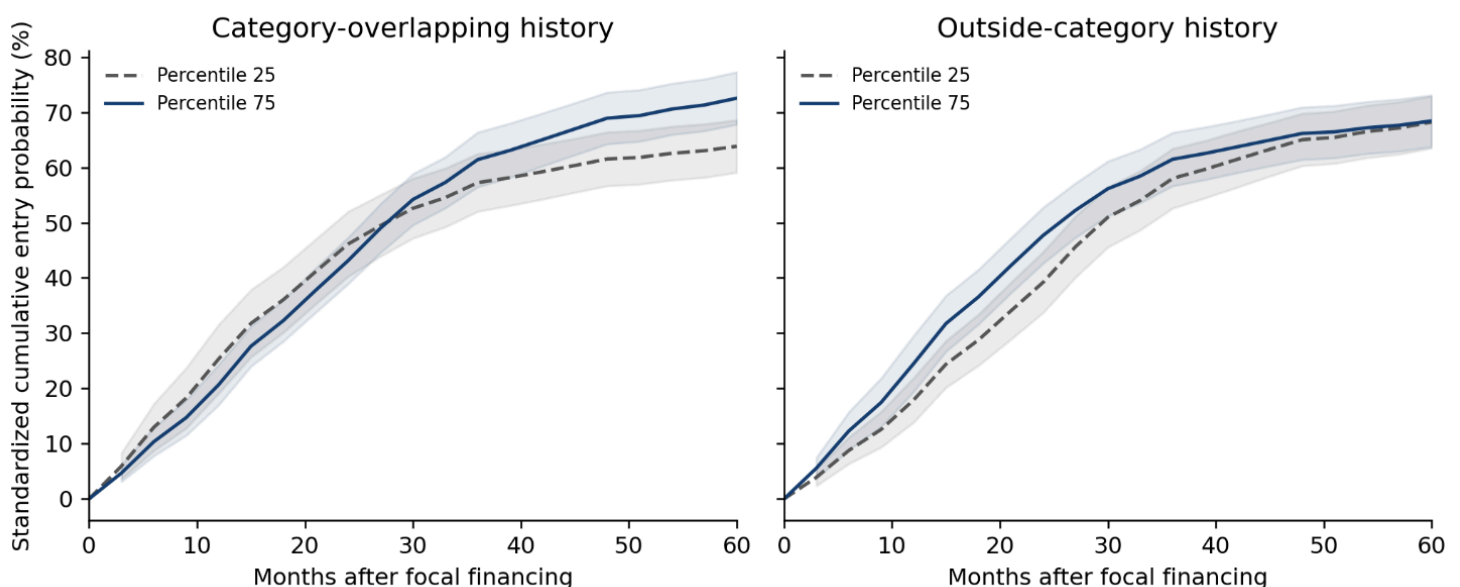


Figure 1

Model-standardized cumulative entry by investor history

Notes: The primary model is estimated on 744 ventures. Predictions use a common population of 576 ventures with complete 60-month observation. Each panel varies one history between its quartiles in this population while holding the other history and controls at each venture's observed values. Shading indicates pointwise 95% intervals. The curves are model-standardized predictions, not effects of assigning investors.

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