How Unique Is Enough? Startups' Market Positioning Relative to Peers and Funding Outcomes in Accelerators

ABSTRACT

Startups in accelerators are evaluated in direct comparison with cohort peers, yet we know little about how a venture's *relative* market position within its cohort is associated with funding outcomes. Prior research offers competing predictions: optimal distinctiveness theory highlights a trade-off between competitive advantage and legitimacy, while entrepreneurial learning emphasizes the benefits of similarity for knowledge acquisition. Using data on 3,205 U.S. startups in 189 cohorts across 26 accelerator programs (2005–2018), along with a matched sample of comparable non-accelerated startups, we measure a venture's cohort market position as its industry similarity to cohort peers. We find an inverted U-shaped relationship between industry similarity and overall funding within two years post-graduation: ventures with moderate distinctiveness raise the most overall capital. In contrast, funding from high-reputation VCs increases with distinctiveness, favoring highly unique market positions. These results reconceptualize cohort effects as relative distinctiveness within the cohort and highlight the critical role of investor attributes—particularly reputation—in shaping funding outcomes.

Keywords: market position, entrepreneurship, accelerator, funding

1. INTRODUCTION

Accelerators are time-limited, cohort-based programs that provide mentorship, structured training, and access to networks in exchange for equity. They culminate in a Demo Day where cohort companies pitch to investors side by side (Cohen et al., 2019a; Hallen et al., 2014; Hallen et al., 2020). In this setting, startups emphasize the uniqueness of their offerings and market position to build competitive advantage and attract funding, but uniqueness is inherently relative. Because financing on Demo Day and in subsequent investments depends not only on venture quality but also on how a startup compares with cohort peers, a venture's "uniqueness" is evaluated less in isolation than in relation to its cohort.

We ask how a startup's uniqueness within a cohort, specifically its market position, relates to post-program funding. We define market positioning as a startup's location in an industry attribute space, represented by its combination of industry categories (Greve, 1996; Nickerson et al., 2001). Unlike established firms, whose industry boundaries and positions tend to be well defined, startups often span multiple industries when describing what they do. For example, IYK is a tech startup that builds tools to digitize physical objects and experiences, enabling brands, creators, and artists to chip, mint, and link creative items to customized digital experiences and, in some cases, convert them into digital assets. By combining blockchain-enabled infrastructure with fashion, music, and platform technologies, IYK creates a distinctive market position that shapes its target customers, value proposition, and business model. A related follow-up question is whether the funding outcome from distinctive market positions may vary depending on who evaluates and funds the startup. We focus on investor reputation as a key investor attribute: high-reputation investors, drawing on extensive experience and strong track records, may rely on their own idiosyncratic criteria and make different funding decisions than the average investors.

To address our first question, we draw on two relevant literatures, optimal distinctiveness and organizational learning, which offer competing yet inconclusive predictions. Optimal distinctiveness research argues that organizations should position themselves to be "as different as legitimately possible" (Deephouse, 1999 p.147). Studies in this tradition examine what constitutes an "optimal" degree of distinctiveness relative to peers across a range of organizational attributes, including strategy (Deephouse, 1999; McNamara et al., 2003), market positioning (Taeuscher and Rothe, 2021), innovation activity (Jennings et al., 2009; Roberts and Amit, 2003), business models (Zott and Amit, 2008), and organizational narratives (Haans, 2019; Taeuscher et al., 2021).

Early work generally supports a balanced view, predicting an inverted U-shaped relationship between similarity and outcomes: moderate similarity enables firms to realize competitive benefits from differentiation while maintaining legitimacy through conformity (e.g., Deephouse, 1999; McNamara et al., 2003; Navis and Glynn, 2010; Roberts and Amit, 2003; Robinson and Phillips McDougall, 2001). More recent research, however, adds a trade-off view, arguing that organizations may benefit from taking a clearer stance—either maximizing distinctiveness to sharpen competitive advantage or maximizing conformity to secure legitimacy—because categorical clarity can reduce stakeholder uncertainty and facilitate resource acquisition, implying a U-shaped relationship (Cennamo and Santalo, 2013; Zott and Amit, 2008).

Another relevant research stream is organizational learning in entrepreneurship because peer learning is an essential part of accelerator program (Avnimelech et al., 2021; Cohen et al., 2019a; Hallen et al., 2014; Hallen et al., 2020). The literature argues that learning from similar peers facilitates access to more relevant and readily transferable knowledge (Lane and Lubatkin, 1998; Levinthal and March, 1993; Miao et al., 2021; Raisch et al., 2009; Reuer and Lahiri, 2014). In particular, early-stage startups often draw quickly on the ideas of peers with similar business models or underlying concepts and incorporate these insights into their own business development (McDonald and Eisenhardt, 2020). Unlike established firms, early-stage ventures tend to worry less about competitive pressure from pursuing similar businesses or products because they are still in a formative phase. Instead, they frequently view peers as a convenient and efficient source of learning. This perspective therefore predicts that a firm's unique market position in accelerators can restrict its opportunities to learn from peers operating in similar industries, ultimately reducing its perceived value to investors.

Given these competing predictions, we adopt an exploratory, question-driven approach rather than advance formal hypotheses (Graebner et al., 2023; Nosek et al., 2018; Sætre and Van de Ven, 2021). We begin with baseline tests of how a startup's market position in a cohort relates to post-program funding, operationalizing market position as its industry similarity to other ventures in the cohort. We then examine contingencies to capture the complexity of market position in a cohort and to adjudicate among the most plausible explanations (Bettis et al., 2014; Boyd et al., 2012). This abductive exploration will help us to find novel correlations between venture's market position and funding outcomes and refine existing literature.

Next, to address our second question, we investigate whether the association between a firm's market position and funding outcomes differs by investor reputation. Reputation is an economic signal that reflects differences in perceived (and sometimes realized) quality based on prominence and a history of high-quality outputs (Pollock et al., 2015). Recent work, particularly in the optimal distinctiveness literature, suggests that evaluators often rely on idiosyncratic criteria when assessing distinctiveness and may disagree about what constitutes "valuable" uniqueness (Hsu et al., 2012; Majzoubi and Zhao, 2023). Such heterogeneity arises because evaluators hold different value systems, expertise (Lamont, 2012), preferences and frames (Pontikes, 2012) (Beunza and Garud, 2007), and goals or motivations (Bowers, 2020).

Venture capital research offers parallel arguments about heterogeneity in funding strategies by VC reputation. High-reputation investors are typically prominent, high-performing actors with a track record of successful investments (Gompers, 1996; Lee and Wahal, 2004; Petkova et al., 2014). Because they face heightened expectations from stakeholders, especially limited partners, high-reputation VCs may pursue "home-run" outcomes by taking on riskier investments with outsized upside potential (DeSantola et al., 2024; Petkova et al., 2014). This distinction is consequential for startups: backing by high-reputation investors can increase a venture's ability to attract subsequent funding and signal quality to the market (Lee et al., 2011; Nahata, 2008). Accordingly, if a firm's market position is differently associated with overall funding versus funding from high-reputation VCs, startups may face a strategic trade-off in choosing their market positioning based on which investors they seek to prioritize.

Using data on 3,205 U.S. startups across 189 cohorts in 26 accelerator programs from 2005 to 2018, and a matched sample of equally sized non-accelerated startups constructed using inverse probability of treatment weighting (IPTW) (e.g. Azoulay et al., 2009; Elfenbein et al., 2013; Hallen et al., 2020; Hirano et al., 2003), we test the relationship between a firm's market-position uniqueness, operationalized as cosine similarity to all peers within its cohort, and the size of funding it receives. Our result shows an inverted U-shaped association between a firm's industry similarity to cohort peers (i.e., the inverse of market-position uniqueness) and the firm's overall funding amount within two years after accelerator graduation. Moderate industry similarity is associated with the highest funding, whereas ventures that are either too similar or too distinctive receive less funding. The pattern holds across both overall investor funding and venture capital funding in larger cohorts. However, investor reputation yields a different pattern in the relationship between market-position uniqueness and funding outcomes. Unlike overall funding, funding from high-reputation VCs such as Andreessen Horowitz and Accel is increasingly associated with distinctiveness, indicating a stronger preference for unique market positions.

Our study contributes to the literature on accelerator cohort effects and to related work on optimal distinctiveness and organizational learning. Building on accelerator research that highlights industry heterogeneity as an important element of cohort effect (Assenova and Amit, 2024; Cohen et al., 2019b), we continue to examine participating startups' industry profiles in studying cohort effects but shift attention to a focal firm's market position relative to its cohort peers. We document two distinct patterns linking within-cohort relative distinctiveness to funding outcomes. This reframes cohort effects as a function of relative distinctiveness within the cohort, rather than cohort composition alone. We also extend optimal distinctiveness research, which has largely focused on established firms within single industries, by examining early-stage startups that span multiple nascent and established industries in accelerator programs, where within-cohort comparison through demo-day narratives and investor attention is especially salient. Our findings of the inverted U-shaped relationship for overall funding and the positive linear relationship for high-reputation funding extend the discussion in the optimal distinctive literature into cross-industry setting. Finally, we contribute to entrepreneurial organizational learning research, which typically emphasizes the benefits of learning from similar peers (McDonald and Eisenhardt, 2020), by shifting the unit of analysis from dyadic similarity to a focal firm's position relative to the entire cohort. We show that learning gains from similarity can be masked when convergence erodes a venture's relative distinctiveness.

In the next setting, we explain our empirical setting and discuss findings.

2. METHODS AND RESULTS

2.1. Context and Data

Our context is U.S. accelerators and their participants located in U.S. from 2005 when the first accelerator program, Y Combinator, launched its first batch, to 2018, considering the timing of funding (in our case, 2 years after graduation) before the Covid Pandemic which shifted most accelerator programs online.

Since the popularity of accelerator programs has produced substantial variation in programs that self-identify as accelerators, we follow the canonical definition of accelerators as structured, time-limited, cohort-based programs that support early-stage startups through mentorship, education, and access to investors, typically in exchange for equity (Assenova and Amit, 2024; Cohen and Hochberg, 2014). Programs generally culminate in a Demo Day, where startups pitch to an audience of investors such as VCs, seed investors, and angels, as well as partners and other stakeholders. Demo Day serves as a focal point for evaluation and comparison because investors assess startups side by side after they have undergone the same training and mentoring process.

We gathered information on accelerators and participating firms from Crunchbase and Seed-DB, initially compiling the data in 2018 and updating it in 2022. Founded in 2007 by TechCrunch, Crunchbase has become a prominent source of startup and investment information (Hallen et al., 2023; Piezunka and Dahlander, 2015; Yu, 2020), providing data on companies (e.g., founding dates, locations, funding histories, industries, and IPO/M&A outcomes), individuals (e.g., founders' education and employment backgrounds), and investors. To support broad coverage, Crunchbase collaborates with more than 400 venture capital firms, accelerators, incubators, and angel investors. User-submitted entries are then reviewed and validated using a combination of human moderation and machine-learning algorithms.

Seed-DB compiles accelerator cohort information and relies on Crunchbase's API to retrieve current firm-level data. We matched company names across Crunchbase and Seed-DB and manually reconciled inconsistencies by visiting company websites and founder profiles. In addition, although Crunchbase offers information on founding teams and often links to founders' LinkedIn pages, missing data remain a concern (e.g., Hallen et al. (2023) report that only 37% of sampled firms had founding-team information in Crunchbase). To mitigate this limitation, one author and a team of research assistants filled data gaps through extensive manual searches of LinkedIn, AngelList, personal websites, and press releases.

Our final dataset comprises 3,205 U.S.-based startups that were no more than five years old at entry and participated in an accelerator for the first time, spanning 189 cohorts across 26 accelerator programs between 2005 and 2018. Consistent with prior work, the dataset includes only accelerators that operated at least four cohorts, enrolled more than four startups per cohort, and had more than 30 participants in total (Yu, 2020).

To evaluate the extent of missing data, we compared our records for Y Combinator, the largest U.S. accelerator, with the program's official membership directory. This comparison revealed a discrepancy of approximately 10%, which we addressed through manual verification and correction. To ensure that the imputation of missing values did not bias our results, we re-estimated all models including observations that were previously excluded and obtained substantively similar findings. We also introduced a data-source indicator variable, which was statistically insignificant and did not affect our results.

2.2. Variables

2.2.1. Market position

In strategy research, market position refers to a firm's decision regarding the types of products or services it offers within a differentiated market (Greve, 1996; Nickerson et al., 2001). In the accelerator context, however, participating startups are often at a very early stage and may not yet have fully developed products or services. Accordingly, we use startups' industry profiles, including multiple industry memberships, as a proxy for market position. In this setting, a startup's unique market position is reflected in how it spans industries and occupies a distinctive position at their intersection.

2.2.2. Dependent variables

We use three types of funding outcomes. First, for general funding outcomes (*Total funding)*, we use the total funding amount from all US investors within two years since the accelerator graduation. The exclusion of foreign investors, albeit rare, helps us to test our ideas within a single institutional context. Second, VC funding amount (*VC funding)* includes the total funding from US VCs within the same 2-year period. In our data, 47.9% of participating startups received VC funding. Third, to assess whether the relationship between market-position uniqueness and funding outcomes varies by investor reputation, we examine funding amounts received from high-reputation VCs. Following a widely used approach in the VC literature, we computed the multi-item, time-varying reputation index developed by Lee et al. (2011). Their index aggregates five indicators capturing a VC's prominence and performance—reflecting visibility, fundraising ability, and exit outcomes: (1) the number of portfolio firms invested in, (2) the total dollars invested in portfolio firms, (3) the total dollars raised, (4) the number of funds raised, and (5) the number of portfolio firms taken public (IPO exits). Each indicator is standardized into a z-score to ensure comparability across components, then aggregated into one composite reputation score. Finally, the composite score is normalized to a 0–100 scale within each year, preserving within-year ranking while enabling comparisons across time. Using this VC reputation score, we created a variable, *Funded by high-reputation VC,* 1 percentile upper limit. The reputation index is highly right-skewed, with most VCs clustered at low scores (median = 13.32) and only a small elite group in the upper tail. The cutoff is especially steep at the top: the score at the 99th percentile is 92.03, but at the 95th percentile, it drops to 49.65. Because reputation falls off quickly below the extreme tail, we use the 99th percentile to identify truly top-tier VCs including Accel, Kleiner Perkins and New Enterprise Associates (NEA). In our sample, we find that these high-reputation VCs do not invest only for well-known accelerators. Their investment records are found almost all accelerators. If a firm received the funding from these highly reputable VCs within 2 years after graduation, it has a value 1, otherwise 0.

2.2.3. Independent variables

We measure a firm's market position within an accelerator by computing the cosine similarity between the vectorized industry-code profile of a focal firm and those of peer firms in the same accelerator cohort (Barlow et al., 2019; Majzoubi et al., 2025). Because each firm can have multiple industry memberships (typically 3–5), we represent each firm as a multi-code industry membership vector. We calculate pairwise cosine similarity between the focal firm and every peer firm, and then average these similarities across all peers to construct our proxy for *Industry similarity*. To examine a potential non-linear relationship, we also include *Industry similarity, squared*.

2.2.4. Control variables

Firm-level controls include *Firm age, Pre-seed,* and *Patent ownership*. Pre-seed record includes whether a firm received pre-seed funding before joining an accelerator program, which positively affects the likelihood of receiving a series A or following-funding (Assenova and Amit, 2024; Hallen et al., 2020). Patent ownership is measured by whether a startup holds a USPTO-granted patent prior to joining accelerator program. In an asymmetric information relationship between a venture and investors, patent can be a good proxy of firm quality and potential to develop an innovative product and service (Haeussler et al., 2014).

At the founding-team level, we control for founding teams' prior education and working experiences. *Founding team, prior job in technology* and *Founding team, prior job in sales/marketing* means whether a founding team member has prior experiences in technology and sales/marketing roles in the past two previous jobs (Hallen et al., 2020). Also, founding team's prior entrepreneurship experiences, *Founding team, serial entrepreneurs*, is added to models (Hallen et al., 2020). Next, we account for the founding team's knowledge depth by identifying whether any founder of a venture had an MBA, JD, technical master's or PhD (*Founding team, advanced degrees*) (Hallen et al., 2020).

To control for accelerator programs' heterogeneity, we add cohort size and a fixed effect of accelerator. For the TechStars which runs both general program and industry-specific program with corporate partners (e.g. TechStar often runs special industry-associated programs, New York Barclays Accelerator, with a focus on fintech), we distinguish by their programs. Lastly, we control for cohort-year and industry-fixed effects using broad industry categories (e.g. software, manufacturing/hardware, life science/healthcare, consumer/retail, finance, others) (Gompers et al., 2009).

2.3. Endogeneity

Since accelerator researchers often face the challenge of selection and treatment effects, we follow prior research and adopt an inverse probability of treatment weighting (IPTW) approach (e.g. ,Assenova and Amit, 2024; Azoulay et al., 2009; Elfenbein et al., 2013; Hallen et al., 2020; Hallen et al., 2023). It reweights the sample to balance observed covariates between treated and untreated firms, thereby approximating a randomized assignment to acceleration and reducing bias from non-random selection. In doing so, we took a similar approach to Yu (2020) and created a control group consisting of startups having similar attributes to a treatment group (accelerated firms) yet never participated in accelerator program. Using firm location (city), business description, industry, founding year, funding history, and founders' undergraduate university, we selected control firms comparable to the treated firms (accelerated startups). After 1-to-1 matching, we estimated propensity scores for accelerator participation and computed inverse probability of treatment weights: $1/p$ for treated firms and $1/(1-p)$ for controls, where p is the estimated probability of selection. These weights account for non-random treatment assignment and mitigate selection bias in subsequent analyses.

IPTW was estimated on the full sample of accelerated and non-accelerated firms; however, our main analysis of market position is conducted on the accelerated sample using IPTW weights.

2.4. Estimation

For overall funding and VC funding amount (DVs: *Total funding, VC funding),* we estimate weighted OLS regressions using inverse probability of treatment weights, clustering standard errors at the accelerator–cohort level to account for within-cohort dependence. Also, to estimate the likelihood of being funded by high-reputation VCs, we use a logit model, clustering standard errors at the accelerator–cohort level.

3. RESULTS

Table 1 reports the descriptive statistics. Our measure of *Industry similarity* has a low mean relative to typical measures based on single-industry classifications such as NAICS, because each firm has multiple industry memberships drawn from the 803 industry categories listed in Crunchbase. Tables 2 and 3 present the main results on the relationship between market-position uniqueness and funding outcomes.

3.1. Overall Funding (from all investors)

Models 1–2 in Table 2 report results for overall funding from all investors. The squared term for industry similarity (*Industry similarity, squared*) is negative and significant ($\beta = -18.216$, $p = 0.036$), indicating a nonlinear relationship between a startup's similarity to peers and funding. To aid interpretation, we follow recommended practice in management research for testing inverted U-shaped relationships by examining the turning point and endpoint slopes (5th and 95th percentiles) and providing a graphical illustration (Haans et al., 2016; Lind and Mehlum, 2010). Figure 1 plots predicted margins from Model 2 over the range of industry similarity (5th–95th percentiles) and confirms an inverted-U pattern. The estimated slope is positive at the 5th percentile (5.67, $p = 0.068$) and negative at the 95th percentile (−4.55, $p = 0.090$), and the turning point lies within the observed range (0.16, $p = 0.000$). Substantively, the effect is economically meaningful. Predicted venture capital funding increases by approximately 55% as industry similarity (i.e. decrease of a firms' uniqueness in market position) rises from 5th percentile to its turning point (≈ 0.16), but then declines by about 25% as similarity increases further to the 95th percentile.

3.2. VC funding

Models 3–4 in Table 2 report results for VC funding that restrict our sample to those who received VC funding (conditional VC funding). In Model 4, we find that the coefficient on industry similarity is positive, while the coefficient on the squared term is negative and statistically significant ($\beta = -13.686$, $p = 0.002$).

However, marginal effect estimates show that at low levels of industry similarity (5 percentile), the marginal effect of similarity on VC funding is positive but statistically indistinguishable from zero (1.30, $p = 0.34$). In contrast, at high levels of similarity (95 percentile), the marginal effect becomes negative and statistically significant (−5.72, $p = 0.00$), indicating that additional similarity substantially reduces VC investment amounts. Also, the estimated turning point of the inverted-U is 0.05 but not statistically distinguishable from zero. The results mean although we find the negative coefficient of *Industry similarity, squared* in the regression table, actual marginal effect is significant only in decreasing part. Also, when we compute effect size, overall, firms at high similarity levels (95 percentile) receive approximately 38 % less VC funding than those at low similarity levels (5 percentile).

Furthermore, since marginal graphs do not support the inverted-U-shape curve in spite of negative coefficient of *Industry similarity, squared,* we suspect that there may be some contingencies. Model 5 indicates that the relationship between a firm's similarity to peers and VC funding is contingent on cohort size: the interaction between industry similarity squared and cohort size is negative. Marginal plots in Figure 3 evaluated at the 25th, 50th, 75th, and 90th percentiles of cohort size show that in small cohorts, there is a downward curve. However, as the cohort size increase, the inverted-U becomes progressively steeper. For example, at the 75th percentile of cohort size (64 startups per cohort), the endpoint slopes are positive at the 5th percentile of similarity (10.34, $p = 0.000$) and negative at the 95th percentile (-23.85, $p = 0.000$), with a turning point at approximately 0.08 ($p = 0.000$), confirming an inverted-U in larger cohorts. Substantively, the effect size for large cohort (75^{th} percentile) is large: predicted funding increases by about 49 % as similarity rises from zero to its cohort-specific optimum (turning point), but then declines sharply; at the 95th percentile of similarity, predicted funding is approximately 88 % lower than at the turning point.

Taken together, the average relationship between industry similarity and VC funding does not exhibit a statistically significant inverted-U. However, our test of cohort size shows that the average null effect masks substantial heterogeneity of VC funding across cohort sizes.

3.3. Funding from high-reputation VCs

Next, Models 6–8 in Table 2 report results for the probability of receiving funding from high-reputation VCs. In Model 7, the squared term of industry similarity is positive and significant ($\beta = 19.189$, $p = 0.002$), and Figure 4 plots an asymmetric inverted U-shaped relationship, with a steeper and more prolonged decline. Endpoint slope tests indicate a negative slope at the 5th percentile (−0.93, $p = 0.004$) and a positive but statistically insignificant slope at the 95th percentile (0.31, $p = 0.271$), with a turning point at approximately 0.20 ($p = 0.000$). This means, while the marginal plot is consistent with a U-shaped pattern, the lack of statistical support for the upward-sloping segment warrants caution. Substantively, the results suggest that funding from high-reputation VCs is most likely when startups occupy a relatively unique market position (i.e., are less similar to peers). The estimated effect size is meaningful: moving from zero similarity to a turning point corresponds to an 8.3 percentage-point decline in the predicted probability, representing a reduction of more than one-third relative to the baseline probability.

In Model 8, we use an alternative, extreme-case measure—*Unique position*, coded as 1 when industry similarity equals zero (no industry overlaps with peers) and 0 otherwise. Startups with a unique position are significantly more likely to receive funding from high-reputation VCs ($\beta = 0.413$, $p = 0.044$). Substantively, predicted probabilities increase from 18.9% to 23.8% when moving from overlap to no overlap, corresponding to about 26% increase relative to the baseline probability (i.e. having similar peers).

3.4. Unconditional VC funding

In Table 3, we estimate the VC funding amount with the full model. The unconditional specification captures whether peer similarity affects access to VC capital, whereas the conditional specification (above in Table 2) isolates how similarity shapes the scale of VC investment once a firm has secured VC funding. We find that industry similarity is not significantly associated with VC funding. The result indicates that peer similarity primarily shapes the allocation of VC capital rather than access to VC funding itself. Next, similarly, we estimate whether a firm received a funding from high-reputation VCs with the full model. This setting allows us to address the question of whether a firm's similarity affects its likelihood of attracting high-reputation VC at all, regardless of whether it receives other VC funding. We find the consist results as we find the downward pattern in conditional funding. The coefficient of interaction term in Model 4 (β= 19.189, p =0.002) is positive and significant while marginal graph illustrates the downward curve. Also, in Model 5, with the alternative term, *Uniqueness*, the result is that same. This implies that high peer similarity reduces access to high-reputation VC investors and continues to constrain their VC involvement even among firms that secure VC funding.

3.5. Supplementary Tests

First, we examined whether funding outcomes differ for industry-focused accelerators. In both models for the overall funding and VC funding, the three-way interaction (*industry similarity squared* × *industry-focused accelerator*) is not statistically significant, suggesting that our results are not driven by accelerators' industry focus. Second, using alternative DVs (whether a firm's total funding within 2 years after graduation cross the threshold (US$500K) from all investors and from VCs), we re-estimated the likelihood of receiving the funding amount; the results show the same patterns. Third, although high-reputation VCs invest across many accelerator programs and we actually find that all accelerators in our sample have experiences of getting funding from the top VCs, one concern is that a prominent accelerator could be driving the findings. To address this, we ran regressions excluding Y Combinator and found that remaining accelerated firms still yields a downward-curving relationship. This implies that high-reputation VCs place greater weight on startups' unique market positions regardless of in which programs the firms are accelerated. Fourth, since high-reputation VCs' investment tends to be centered around ventures in hot markets (e.g. AI startups in 2020s) (DeSantola et al., 2024), our result may be driven by an industry boom, not by a firm's specific market position. To test this, we gathered information on hot technologies from the market research institution, Gartner's top 10 strategic technology trends annual reports, and mapped whether a firm's business description belonging to the list. However, when we added this variable, *hot market,* our results hold, while the variable is not significant. This attenuates our concerns about high-reputation VCs' preference of hot industries.

4. DISCUSSION

Our findings show an inverted U-shaped association between a startup's market position and both overall funding and VC funding, particularly in larger cohorts, whereas funding from high-reputation VCs follows a downward pattern with industry similarity, indicating a preference for more distinctive positions. Together, these results show that cohort-relative market position in accelerators is associated with different funding outcomes depending on investors' key attributes such as reputation. Accordingly, we interpret our empirical findings through the lenses of optimal distinctiveness and entrepreneurial learning.

First, inverted-U-shape for overall funding (measured by total funding amount) provides two plausible explanations: Consistent with a balance view in optimal distinctiveness literature, participating ventures distinct themselves from peers in the same cohort, but not too far to be legitimate. Investors, in general, are prone to be attracted to startup with unique profiles, but not too unfamiliar, because their judgement is relative comparison across participating startups. In this case, investors may avoid investing in startups that are overly distinctive, as extreme distinctiveness can trigger doubts about market fit or appropriateness in an established category, increasing perceived risk. At the same time, they may discount startups that are too similar, because they appear undifferentiated, crowded, or offering limited upside. Also, from organizational learning perspective, having good numbers of peers in similar industries allows the firms to absorb relevant and useful business ideas such as opportunity identification, business-model refinement, and scaling under uncertainty (Miller et al., 2024; Santamaria and Breschi, 2025). However, increasing similarity in cohort possibly makes the peer learning less novel, even redundant, while escalating concerns about competition among peers.

Second, unlike overall funding across all investor types, the relationship between market-position uniqueness and VC funding becomes more sharply inverted U-shaped as cohort size increases. One plausible explanation is that professional investors, particularly VCs who manage large funds, may rely on direct benchmarks when evaluating ventures. In larger cohorts, peer comparison is more salient because investors can more easily assess startups against a broader set of peers in similar markets. As a result, VCs may place greater weight on the balance between differentiation and legitimacy when cohort-based comparisons are more visible.

Third, high-reputation VCs' strong preference for investing in unique firms indicates heterogeneity of VC investment based on their past performance. Our strong support for the linear relationship (negative effect of industry similarity, the positive effect of extreme case where firms have no industry overlaps with peer firms at all), indicates that top-tier VCs (in our context, top 1% VCs) have different investment strategy when accessing accelerated firms. This could be explained by high-reputation VCs' priority to pursue the venture's home-run even if it is risky (Petkova et al., 2014). Or, unlike overall pattern of inverted-U-shape in VCs, high-reputation VCs may have a clear preference for potential competitiveness because they consider legitimacy less important based on their own assessment. Also, from the organizational learning perspective, their rich experiences and knowledge also make their own judgement on the quality and unique of ventures more than what the venture earns from peers such as shared market knowledge.

Contributions

Our study contributes to the literature on accelerator cohort effects and to related work on optimal distinctiveness and organizational learning. First, building on accelerator research emphasizing industry heterogeneity and the value of collective diversity for cohort effects (e.g., Assenova and Amit, 2024; Cohen et al., 2019b), we shift attention from cohort-level composition to a focal firm's market position relative to its cohort peers. This relational approach captures within-cohort relative distinctiveness rather than a firm's exposure to industry diversity in the cohort, and allows us to examine how differences between a focal firm and its peers shape funding outcomes. By shifting the reference point from cohort-level diversity to within-cohort comparison, we extend prior research on accelerator cohorts without negating its core insights.

Second, whereas optimal distinctiveness research has largely examined firms' positions within a single industry, often focusing on established firms in traditional industry settings, we extend this literature by studying early-stage startups that span multiple nascent and established industries. The accelerator context, which naturally fosters within-cohort comparison through demo-day narratives and investor attention, also provides a useful setting to examine how optimal distinctiveness operates across industries. Our results, showing an inverted U-shaped relationship for overall funding and a positive linear relationship for funding from high-reputation investors, indicate that the benefits of distinctiveness are context dependent (i.e. cross-industry comparison in accelerators) and reveal new patterns for early-stage startups that have not been examined in prior optimal distinctiveness research.

Third, organizational learning research, particularly in entrepreneurial settings, emphasizes the positive performance effects of learning from similar peers pursuing similar ideas and business models (e.g., McDonald and Eisenhardt, 2020). We extend this perspective by shifting the unit of analysis from dyadic firm-to-peer similarity to a focal firm's position relative to the entire cohort. Our findings offer limited support for dyadic peer learning as a primary explanation for funding outcomes. Rather, they suggest that while similarity may facilitate learning, its benefits can be offset in accelerator settings when convergence within the cohort reduces a venture's relative distinctiveness and, consequently, its attractiveness to external evaluators such as investors. Moreover, because our dependent variables capture funding amounts, they primarily reflect investor evaluation, so learning-related benefits may be overshadowed and not fully captured as accumulated organizational knowledge.

This research also offers practical guidance for accelerator managers and founders. Because accelerators build cohorts as portfolios rather than selecting startups solely on absolute quality, our findings suggest how managers can align cohort composition with program goals. For example, an effective portfolio may emphasize startups that are distinctive but not too distant from cohort peers, while including a small number of highly distinctive ventures. Or, if the goal is to attract top-tier VCs, managers may want to prioritize exceptionally distinctive startups, albeit with greater caution. For founders, our research shows that clarifying market position is a key milestone not only for identifying customers and shaping products and services, but also for determining which investors to target. Not all ventures pursue top-tier VC funding, particularly given potential concerns about legitimacy and reduced opportunities for peer learning. For these ventures, a balanced market position can yield the strongest overall funding prospects. More broadly, our results can help founders prioritize a fundraising strategy during the program and position the venture accordingly, focusing on the investor mix that best fits their early-stage objectives.

Our research is not without limitations, and it opens up several avenues for future work. First, because we could not directly observe or test the dynamics of peer interactions, we encourage future research to adopt methods that can more directly examine the underlying mechanisms, particularly those related to peer learning. Experimental designs and ethnographic approaches, among others, could be particularly useful. Second, building on our findings, it would be valuable to investigate how firms' unique market positions translate into performance within their respective industries. This line of inquiry would require a longer observation period that extends to when firms introduce tangible products and services to the market, given that our study focuses on very early-stage startups.

Taken together, our study shows how a firm's market position relative to cohort peers is associated with accelerator funding outcomes, revealing two distinct patterns. Overall funding is highest for firms that are distinctive yet close to their peers, while high-reputation VC investment favors highly distinctive ventures. Overall, our study advances accelerator research by identifying within-cohort relative market position as a key dimension of accelerator success, and it extends research on optimal distinctiveness and organizational learning by demonstrating how these mechanisms may operate in accelerator settings.

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Figure 1. Overall Funding

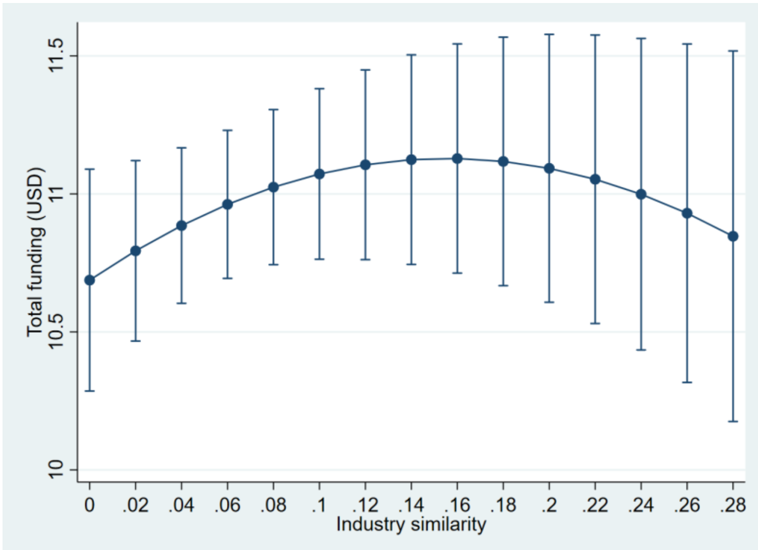

Figure 2. VC funding (conditional on receiving VC funding)

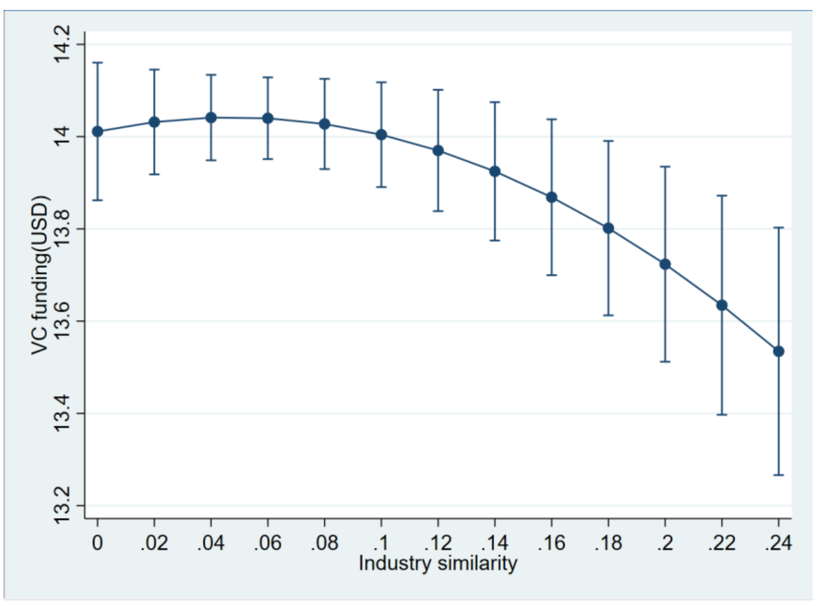

Figure 3. VC Funding by Cohort Size (conditional funding)

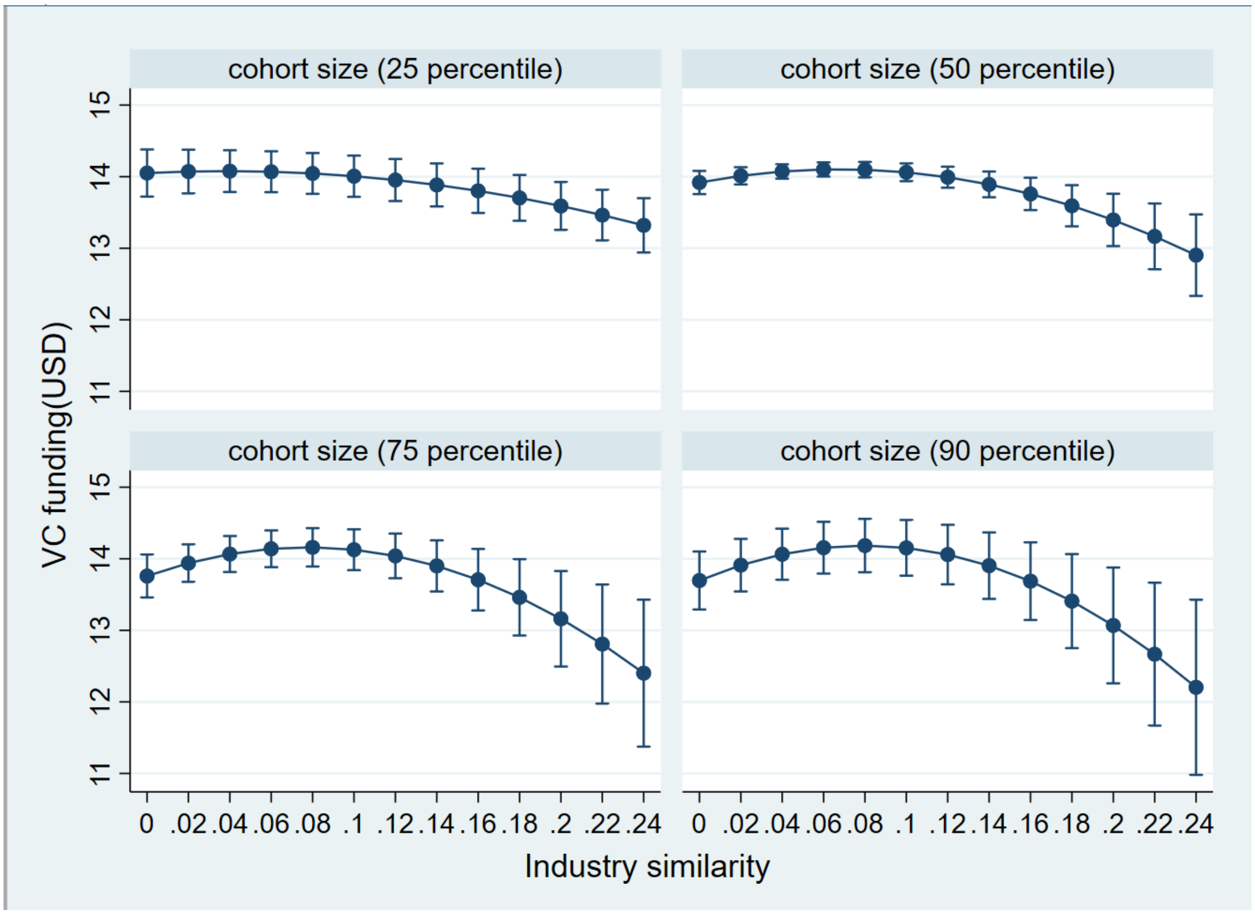

Figure 4. Funding by high-reputation VCs

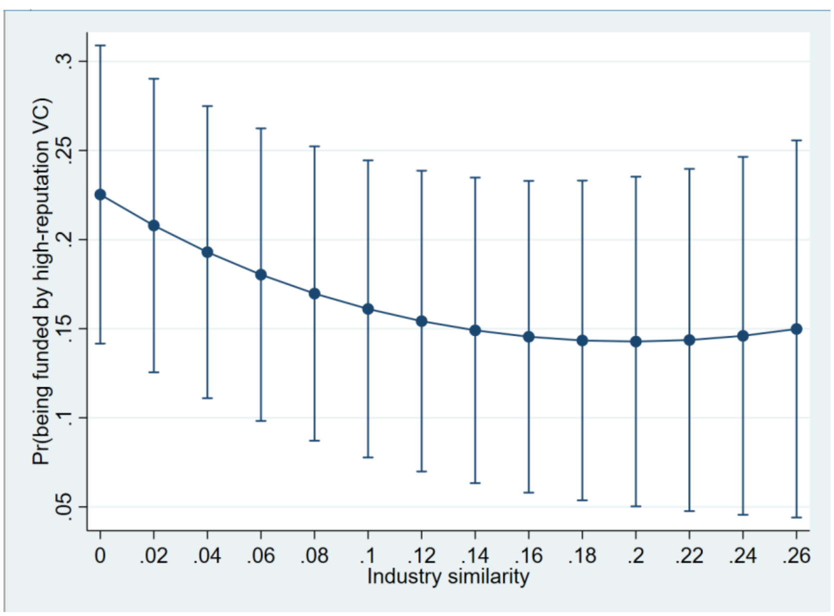

Table 1. Descriptive Statistics

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1	Total funding	10.91	6.04	1											
2	VC funding	8.78	6.89	0.79	1										
3	Funded by high-reputation VC	0.17	0.38	-0.04	-0.06	1									
4	Industry similarity	0.07	0.09	-0.04	-0.05	-0.11	1								
5	Cohort size	3.33	0.88	0.14	0.11	0.39	-0.38	1							
6	Firm age	1.96	0.99	0.10	0.05	0.14	-0.07	0.14	1						
7	Pre-seed	0.34	0.47	0.17	0.15	-0.10	0.02	-0.12	0.22	1					
8	Patent ownership	0.07	0.25	0.04	0.04	0.00	-0.01	0.03	0.03	0.01	1				
9	Founding team, prior job in technology	0.17	0.37	0.00	0.03	0.03	0.03	-0.01	-0.05	-0.02	0.01	1			
10	Founding team, prior job in sales/marketing	0.03	0.18	0.00	0.03	-0.05	0.01	-0.04	-0.02	0.03	0.02	0.07	1		
11	Founding team, serial entrepreneurs	0.37	0.48	0.10	0.13	-0.05	0.01	-0.04	-0.08	0.00	0.04	0.13	0.04	1	
12	Founding team, advanced degrees	0.23	0.42	0.11	0.10	0.02	0.03	0.02	0.02	0.05	0.02	0.07	0.02	0.07	1

Note: Variables 1-2, 5 are logged due to skewness.

Table 2. Main results for Industry similarity and Funding Outcomes (Conditional VC funding in Models 3-8)

	Total funding (USD)		VC funding (USD)			Funding from high-reputation VC		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Industry similarity	0.225	5.669	-2.546	1.299	-12.795	-1.960	-7.608	
	[0.884]	[0.068]	[0.002]	[0.344]	[0.009]	[0.272]	[0.001]	
Industry similarity, squared		-18.216		-13.686	57.968		19.189	
		[0.036]		[0.002]	[0.006]		[0.002]	
Cohort size	0.967	0.979	-0.027	-0.036	-0.181	0.172	0.112	0.229
	[0.026]	[0.023]	[0.868]	[0.822]	[0.293]	[0.876]	[0.918]	[0.835]
Industry similarity x Cohort size					5.542			
					[0.001]			
Industry similarity, squared x Cohort size					-29.852			
					[0.001]			
Unique position (Industry similarity= 0)								0.413
								[0.044]
Firm age	-0.057	-0.057	-0.160	-0.158	-0.154	0.283	0.285	0.284
	[0.569]	[0.564]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
Pre-seed	2.011	2.020	0.049	0.054	0.058	-0.479	-0.492	-0.480
	[0.000]	[0.000]	[0.601]	[0.567]	[0.537]	[0.013]	[0.011]	[0.013]
Patent ownership	0.059	0.053	0.247	0.247	0.226	-0.031	-0.010	-0.052
	[0.889]	[0.899]	[0.123]	[0.117]	[0.150]	[0.876]	[0.961]	[0.798]
Founding team, prior job in technology	0.110	0.108	0.329	0.314	0.297	0.544	0.535	0.534
	[0.740]	[0.746]	[0.004]	[0.006]	[0.009]	[0.000]	[0.000]	[0.000]
Founding team, prior job in sales/marketing	0.259	0.270	-0.349	-0.351	-0.359	-0.851	-0.840	-0.853
	[0.671]	[0.655]	[0.075]	[0.066]	[0.050]	[0.024]	[0.017]	[0.019]
Founding team, serial entrepreneurs	0.791	0.780	0.128	0.127	0.127	-0.205	-0.192	-0.188
	[0.000]	[0.000]	[0.064]	[0.066]	[0.067]	[0.102]	[0.127]	[0.134]
Founding team, advanced degrees	1.169	1.159	0.227	0.227	0.232	0.068	0.073	0.073
	[0.000]	[0.000]	[0.018]	[0.018]	[0.014]	[0.596]	[0.573]	[0.567]
Constant	1.864	1.700	15.590	15.584	15.884	-5.039	-4.851	-5.417
	[0.003]	[0.007]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
Cohort year, fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Accelerator program, fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry, fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IPTW weight	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,205	3,205	2,022	2,022	2,022	2,978	2,978	2,978
R-squared	0.191	0.192	0.255	0.259	0.264			

Note 1: p-values in brackets.

Table 3 Results for Unconditional VC funding

	VC funding (USD)		Funding from high-reputation VC		
	Model 1	Model 2	Model 3	Model 4	Model 5
Industry similarity	-1.631	1.103	-1.960	-7.608	
	[0.367]	[0.760]	[0.272]	[0.001]	
Industry similarity, squared		-9.148		19.189	
		[0.368]		[0.002]	
Unique position (Industry similarity= 0)					0.440
					[0.034]
Cohort size	1.316	1.322	0.172	0.112	0.217
	[0.002]	[0.002]	[0.876]	[0.918]	[0.843]
Firm age	-0.287	-0.287	0.283	0.285	0.286
	[0.019]	[0.019]	[0.000]	[0.000]	[0.000]
Pre-seed	1.724	1.729	-0.479	-0.492	-0.486
	[0.000]	[0.000]	[0.013]	[0.011]	[0.012]
Patent ownership	-0.041	-0.043	-0.031	-0.010	-0.067
	[0.934]	[0.929]	[0.876]	[0.961]	[0.739]
Founding team, prior job in technology	0.269	0.268	0.544	0.535	0.511
	[0.452]	[0.454]	[0.000]	[0.000]	[0.000]
Founding team, prior job in sales/marketing	0.630	0.635	-0.851	-0.840	-0.825
	[0.285]	[0.279]	[0.024]	[0.017]	[0.025]
Founding team, serial entrepreneurs	1.073	1.068	-0.205	-0.192	-0.175
	[0.000]	[0.000]	[0.102]	[0.127]	[0.154]
Founding team, advanced degrees	1.397	1.392	0.068	0.073	0.089
	[0.000]	[0.000]	[0.596]	[0.573]	[0.494]
Constant	0.041	-0.041	-5.039	-4.851	-5.478
	[0.952]	[0.952]	[0.000]	[0.001]	[0.000]
Cohort year, fixed effect	Yes	Yes	Yes	Yes	Yes
Accelerator program, fixed effect	Yes	Yes	Yes	Yes	Yes
Industry, fixed effect	Yes	Yes	Yes	Yes	Yes
IPTW weight	Yes	Yes	Yes	Yes	Yes
Observations	3,205	3,205	2,978	2,978	2,978
R-squared	0.183	0.184			

Note 1: p-values in brackets