Signalling vs. Support: The Strategic Design of Start-up Accelerators

Sven Werner
Schumpeter School of Business and Economics, University of Wuppertal, Germany

sven.werner@uni-wuppertal.de

Abstract: Start-up accelerators play an important role in providing resources to new ventures through mentoring, education, peer interaction, certification, networking, and (in-kind) financing. Numerous studies have described different design choices of accelerators and empirically evaluated their effectiveness on start-up performance, e.g., revenue growth and funding success. However, the determinants and strategies shaping an accelerator's design have been underexplored, as existing studies predominantly treat the design as exogenous. This paper addresses this gap by developing a formal model that conceptualises accelerator design as an endogenous, strategic response to environmental parameters such as the quality and number of applying ventures. The model considers an accelerator that selects a cohort from a pool of heterogeneous start-ups with unobservable quality and supports the selected start-ups through training. The accelerator can exert effort to improve the precision of noisy quality signals (screening) and allocate resources to post-entry support to selected ventures. Both activities incur costs and are constrained by a fixed budget. The accelerator maximises the expected post-program cohort quality, taking into account the trade-off between improving selection accuracy (which increases the perceived quality of start-ups through signalling) and directly supporting selected start-ups (which directly improves the quality of participants), yielding closed-form expressions for the optimal accelerator design. Solving the model for the Subgame Perfect Bayesian Equilibrium, we show that the optimal design critically depends on the entrepreneurial context, such as the share of high-quality start-ups and the selectiveness of the program (cohort size relative to applicant pool size). We find that when high-quality applicants are scarce, screening effort declines and more resources are allocated to post-entry support, as the returns to screening are relatively low. Conversely, the model shows that as program selectiveness increases, accelerators invest more in screening to extract maximum value from limited cohort slots. These comparative statics yield empirically testable predictions and offer practical implications for accelerator managers, suggesting that design should adapt dynamically to changes in the applicant pool and program maturity. The paper contributes to the accelerator literature by providing a strategic explanation for observed variation in program design and resulting effectiveness. Thus, it lays a foundation for future theoretical extensions and empirical validation aimed at refining our understanding of entrepreneurship support organisations.

Keywords: Accelerator, Start-ups, Strategic Resource Allocation, Signalling, Entrepreneurship Support Organisation, Incubator

1. Introduction

Accelerators are important entrepreneurial support organisations that provide start-ups with a range of resources through a structured, cohort-based program over a fixed time period (Cohen and Hochberg, 2014) to help them overcome constraints of their environment (Amezcua et al., 2013; Bergman and McMullen, 2022). Accelerators are a growing phenomenon with over 6,500 programs globally (Dealroom, 2025). Reflecting this growing relevance, research on accelerators has concentrated around two themes: First, various papers focus on empirically assessing the effectiveness of accelerators on venture outcomes such as revenue growth and investment attraction, producing a broad spectrum of empirical results ranging from large positive effects on start-up performance (Gonzalez-Uribe and Reyes, 2021), to the modest positive impact (Assenova and Amit, 2024; Gonzalez-Uribe and Leatherbee, 2018; Hallen et al., 2023), to no effect (Cusolito et al., 2021; Lall et al., 2020), and even a negative impact (Yu, 2019). In parallel, a second research stream has focused on conceptualising the design characteristics of accelerators and identifying the mechanisms how accelerators support start-ups partly explaining heterogeneity in the above outcomes (Cohen et al., 2019; Hallen et al., 2020). Such mechanisms include capacity building through training, network expansion, (in-kind) financing, and certification, often called quality signalling (Avnimelech et al., 2024).

However, despite advances in describing different accelerator designs and conceptualising their impact mechanisms, existing scholarship consistently treats accelerator designs as exogenous, contributing to the "limited theoretical development" (Bergman and McMullen, 2022) within the accelerator literature. As a result, prior studies largely abstract away from analysing the strategies and determinants of the accelerator design. For example, questions on optimal resource allocation remain unaddressed, such as what drives an accelerator to allocate more resources toward sophisticated pre-entry selection procedures—for instance, multi-stage expert interviews and extensive due diligence, as opposed to investing post-entry in support of admitted start-ups through more extensive tailored training and mentorship programs.

Addressing this gap, this paper introduces a formal model to examine the strategic design decision accelerators make between their effort for pre-entry cohort selection versus post-entry support for selected start-ups. Specifically, the model captures the strategic trade-offs reported by accelerator managers by assuming that start-ups vary in latent quality, quality signals received during selection are inherently noisy, and that the effectiveness of post-entry training and support comes at an incremental cost (Hallen et al., 2020). Solving for the equilibrium of this model highlights an important duality: pre-entry selection and post-entry support investments operate as budgetary substitutes, where increased spending on one limits resources for the other, but act as strategic co-determinants of the overall effectiveness of the accelerator on the cohort's venture outcomes.

Further, I show that accelerators strategically adapt their designs to shifting environmental conditions. In particular, accelerators increase their pre-entry selection effort and reduce post-entry support when the applicant pool contains a higher proportion of high-quality ventures, thereby elevating the returns to more rigorous screening, i.e., the chance of identifying high-quality start-ups. By contrast, when the ratio of selected cohort size to total applicants increases, reflecting reduced capacity constraints, accelerators strategically lower pre-entry effort and allocate more resources towards supporting the admitted start-ups directly, because each start-up represents a smaller fraction of the cohort and, hence, reduces the cost of the selection of a low-quality start-up. These endogenously driven differences in design choices lead to differences in the observed effect of the accelerator on venture outcomes and, thus, provide a novel explanation for the heterogeneity of observed design choices and empirical results on accelerators' effectiveness.

The paper contributes to the accelerator literature in multiple dimensions. Theoretically, it advances understanding of how strategic decisions drive accelerator design and the resulting effectiveness. Empirically, our model generates clear, testable predictions that future research can empirically validate, thereby refining insights into the interplay between accelerator environments and strategic design choices. Practically, I offer actionable guidance for accelerator managers on optimising resource allocation decisions in response to changes in applicant pool characteristics and other environmental dynamics.

The remainder of the paper is structured as follows: Section 2 introduces the formal model. Section 3 presents the analyses of the model, including comparative statics analyses. Finally, Section 4 discusses the theoretical and practical implications of our findings and outlines avenues for future research.

2. The Formal Model

This paper develops a stylized but analytically tractable model of how start-up accelerators strategically allocate limited resources between two core functions: (i) pre-entry screening, which aims to reduce information asymmetries via more precise signals on applicants' quality, and (ii) post-entry support (e.g., training, networking, financing), which enhances the actual capabilities and quality of selected start-ups.

The model builds on the idea that start-up quality is initially private information, and external actors—especially investors—do not directly observe a start-up's type. Instead, they observe whether a start-up was accepted by the accelerator. This introduces an important signalling function: the accelerator selection acts as a certification mechanism that reduces adverse selection and enables subsequent success, e.g., financing from investors, new customer relations. Crucially, this quality signal is not exogenous but the result of a costly effort by the accelerator to identify high-quality ventures. On the other hand, accelerators also provide post-selection support that directly increases start-ups' quality. Examples include mentorship, access to financing networks, business development training, or technical assistance. These investments improve actual start-up capabilities and hence increase the post-accelerator quality of the cohort.

We model the accelerator as facing a strategic trade-off between investing in better screening (which enhances the perceived quality of the accepted cohort via more precise signal-based selection) versus investing in more post-entry support (which directly increases the quality of selected ventures regardless of their initial type). The optimal balance depends on structural parameters such as the size of the applicant pool, the share of high-quality applicants, and the desired cohort size.

Start-up types and signalling technology. More formally, we consider an accelerator that receives applications from n start-ups. Each start-up has a quality which is binary and privately known to the start-up. There are high-quality start-ups (H) which have true quality 1, while low-quality start-ups (L) have quality 0. The accelerator knows the share of high-quality start-ups across the population of applicants a similar to knowing the average quality of start-ups in its environment (Chowdhury et al., 2019). To reduce informational asymmetries, the accelerator can exert screening effort $e \in [0,1]$ to generate a noisy signal about each start-up's quality. High-quality start-ups always produce a positive signal, denoted S_H, while low-quality start-ups generate a positive signal with probability $1 - e$, and a negative signal S_L with probability e. Hence, higher values of e indicate more precise screening, reducing the false positive rate, e.g., through more intensive in-person interviewing of start-ups. The selection process, such as review of written applications or conducting interviews, typically has limited economies of scale and, hence, is assumed to be linear.

Post-entry support and budget. After screening, the accelerator selects c start-ups for its cohort. The accelerator allocates support magnitude s to each selected start-up. Post-entry support increases the quality of each start-up additionally by s, regardless of initial type. The total budget b must cover both the cost of pre-entry screening all applicants and the cost of post-entry support for the admitted cohort. Formally, the budget constraint is given by $b = n \cdot e + c \cdot s$, viewing both e and s in monetary terms. Here, b, c and n are assumed to be exogenous, e.g., defined prior to the budget allocation by the sponsor.

Accelerator's objective. The accelerator's objective is to maximise the total post-program quality of its selected cohort, defined as the sum of the initial quality of selected start-ups plus the additive benefit of support.

Timing. The timing of the game is as follows:

1. Type realisation and applications: Each start-up is randomly assigned a type H or L by nature and n start-ups apply to the accelerator. Note that the order of this does not influence the game as start-ups do not act strategically here (e.g. implicitly assuming application costs for the accelerator are 0).
2. Pre-entry screening: The accelerator chooses the screening effort e, paying cost $n \cdot e$. Each start-up generates a signal conditional on its type.
3. Selection: Based on observed signals, the accelerator selects c start-ups into the cohort.
4. Post-entry support: The accelerator chooses the level of post-entry support s, paying $s \cdot c$, in line with its budget constraint.

3. Analysis

3.1 Equilibrium Characterisation

The accelerator's optimisation problem is solved via backward induction. The equilibrium is a Subgame Perfect Bayesian Equilibrium entailing sequentially rational strategies and belief updating consistent with Bayes' rule given the stochastic signal process.

Stage 3: Post-entry support. Given the screening effort e, the accelerator optimally allocates the entire remaining budget across the c selected start-ups, yielding support intensity $s^*(e) = \frac{b-n \cdot e}{c}$. This is optimal because the accelerator aims to increase the total post-acceleration quality of selected start-ups and has no incentive to not spend its budget.

Stage 2: Selection. High-quality start-ups always produce a positive signal, while low-quality start-ups do so with probability $1 - e$. Hence, the expected fraction of high-quality start-ups among those with a positive signal is: $f(e) = \frac{a}{1-(1-a) \cdot e}$ which respectively is also the expected quality of a start-up with signal S_H. For the accelerator, it is always preferable to select a start-up with a signal S_H having expected quality $f(e)$ over one with signal S_L having quality 0, as subsequent support effectiveness is independent of start-up's quality. Hence, if the number of start-ups with a positive signal exceeds c, the accelerator randomly selects c from this pool. Otherwise, it supplements the cohort with start-ups that received a negative signal. Subsequently, we restrict our attention to the case where there are sufficient start-ups yielding a high-quality signal in expectation, formally assuming $a \cdot n + (1 - a) \cdot n \cdot (1 - e) \geq c$, which seems realistic considering that Assenova & Amit (2024)'s sample of +350 accelerators contains roughly twice as many start-ups with positive signals as capacity on average.

Stage 1: Pre-entry screening. The accelerator maximises the post-acceleration cohort quality. $Q(e)$, which includes the pre-entry quality $f(e)$ and received support $s^*(e)$ for all selected start-ups by choosing the screening effort e:

$$max_e \, Q(e) = c \cdot \left(f(e) + s^*(e)\right) = c \cdot \left(\frac{a}{1-(1-a)\ e} + \frac{b - n\, e}{c}\right)$$

Intuitively, the accelerator faces a trade-off between increasing the pre-entry quality through higher screening effort and increasing post-entry quality through direct support of selected start-ups. Notably, the mechanisms through which start-ups benefit from acceleration are markedly different: With higher pre-entry screening, start-ups benefit from higher quality signals through certification to the outside world, e.g., investors. While with higher post-entry support, start-ups directly benefit from measures improving their quality, e.g., training.

Formally, differentiating with respect to e, the first-order condition is:

$$-n + \frac{ca(1-a)}{[1-(1-a)e]^2} = 0$$

Hence, in an interior equilibrium solution the optimal pre-entry screening effort $e^*$is:

$$e^* = \frac{1 - \sqrt{\frac{ca(1-a)}{n}}}{1-a}$$

However, this expression may lie outside the feasible interval $[0,1]$ in which case, the solution reaches a corner. These corner solutions offer meaningful economic interpretation. If the applicant pool is very large relative to the cohort size and the share of high-quality start-ups is modest, screening becomes prohibitively expensive. In this case, the marginal return to effort is low, since few high-potential start-ups exist to identify, and the marginal cost is high, as screening must be applied to many applicants. The accelerator then optimally sets $e^* = 0$, allocating the full budget to post-entry support. Formally, this occurs when $a(1-a) \leq \frac{n}{c}$.

Conversely, the optimal solution reaches the upper boundary $e^* = 1$ when the unconstrained solution exceeds 1. This occurs when $\frac{1-a}{a} \leq \frac{n}{c}$. This means that the accelerator screens maximally when the share of high-quality applicants is sufficiently large relative to its selectiveness: a small cohort drawn from a strong pool justifies extensive screening to extract top performers. For intermediate values of n, c, and a the interior solution applies.

3.2 Comparative Statics

We now perform comparative statics to examine how the accelerator's optimal screening intensity e^* in an interior solution varies with two critical parameters: (1) the selectiveness of the accelerator, measured as the cohort-to-applicant ratio $\gamma = \frac{c}{n}$, and (2) the prior share of high-quality start-ups a in the applicant pool. Using γ, the optimal screening intensity rewrites to $e^* = \frac{1-\sqrt{\gamma a(1-a)}}{1-a}$.

First, we examine how selectiveness affects optimal screening taking the derivative of e^* with respect to selectiveness γ:

$$\frac{\partial e^*}{\partial y} = -\frac{1}{2(1-a)} \cdot \frac{a(1-a)}{\sqrt{y\, a(1-a)}} = -\frac{1}{2} \cdot \frac{\sqrt{a(1-a)}}{(1-a)\sqrt{y}}$$

Since all terms $a, \gamma \in (0,1)$ are strictly positive, the derivative clearly is strictly negative $\frac{\partial e^*}{\partial y} < 0$. Hence, the screening effort strictly decreases with higher γ (implying lower selectiveness). When the accelerator has a higher cohort size relative to the applicant pool (lower selectiveness through larger γ), the marginal harm of admitting a false positive decreases. Each admitted start-up is less costly in terms of the opportunity cost of a cohort slot, thus reducing the incentive for rigorous screening and instead increasing the incentive to invest in post-entry support. Conversely, a more selective accelerator (lower γ) intensifies its screening effort, since each false positive now represents a more significant loss of scarce cohort capacity.

Second, we examine how changes in prior quality a affect optimal screening. Differentiating the

optimal effort $e^*(y, a)$ with respect to a yields after refactoring:

$$\frac{\partial e^*}{\partial a} = \frac{2\sqrt{y\, a\,(1-a)} - y\,(1-a)}{(1-a)^2}$$

Since the denominator is always positive for $a \in (0,1)$, the sign of the derivative is determined by the numerator. Rearranging this condition yields a clear threshold:

$$\frac{\partial e^*}{\partial a} > 0 \quad \Leftrightarrow \quad a > \frac{\gamma}{\gamma + 4},$$

$$\frac{\partial e^*}{\partial a} < 0 \quad \Leftrightarrow \quad a < \frac{\gamma}{\gamma + 4}.$$

These conditions reflect the following intuition: When the share of high-quality applicants is very low, the marginal benefit from screening—stemming from identifying additional high-quality start-ups and excluding low-quality ones—is initially small and thus remains below the constant marginal cost of screening, that is the opportunity cost of investing the money instead in post-entry support. As a consequence, optimal screening declines further as applicant quality improves slightly, since the net payoff remains negative. However, as applicant quality surpasses a critical threshold (determined by program selectiveness), the marginal benefit from identifying additional high-quality start-ups rises above the constant marginal cost as the chance of identifying additional high-quality start-ups and excluding low-quality ones increases. Beyond this point, the accelerator optimally increases screening effort, as each additional unit of effort now yields a positive net return. Eventually, as screening effort reaches its natural maximum, the optimal effort levels off. This interplay—low marginal benefit at very low applicant quality, rising marginal benefit beyond a critical threshold, and eventual flattening as effort hits its maximum—generates a U-shaped pattern of optimal screening effort in response to changes in applicant quality. Due to space constraints, we restrict our attention to the formal comparative statics with respect to selection effort. In the next section, we highlight some intuition with regards to the comparative statics with respect to post-entry support.

3.3 Numerical Illustration of Equilibrium

To visualize the accelerator's equilibrium behaviour, Figure 1 provides a numerical illustration of the comparative statics derived above. The two panels show how optimal screening effort e^* and post-entry support s^* jointly respond to variation in (a) the selectiveness of the accelerator, γ, and (b) the share a of high-quality start-ups in the applicant pool. These simulations illustrate the closed-form results by highlighting how the trade-off between screening and support unfolds in equilibrium under different environmental conditions.

Panel (a) varies selectiveness by increasing cohort size c, holding the number of applicants fixed. The prior share of high-quality start-ups is set to a relatively low value of $a = 0.05$, reflecting an ecosystem where few high-potential ventures are present. As selectiveness decreases (i.e., γ increases), the value of screening falls, as predicted and explained in the previous section. While a larger share of the budget is allocated towards post-entry support, the support that one start-up receives s^* also declines because the support is distributed across a larger cohort of start-ups. This pattern illustrates a key insight from the model: when cohort slots are relatively abundant, the accelerator finds it optimal to lower its gatekeeping intensity and invest more in downstream support. This might be particularly relevant for newer accelerators having a lower reputation and not attracting as many applicants (Cohen et al., 2019).

Panel (b) complements this by varying the prior share of high-quality start-ups a while holding selectiveness fixed at $\gamma = 0.2$. The results trace a U-shaped response of screening effort to changes in applicant pool quality, analytically described above. This is accompanied by an inverse-U-shaped support-level for selected start-ups, simply by the changed incentives for selection effort and determined by the budget constraint.

These numerical simulations illustrate how the accelerator's design choices emerge endogenously from trade-offs between information acquisition (via screening) and direct capability-building (via support), and how these choices respond systematically to the characteristics of the applicant pool and the selectiveness of the program.

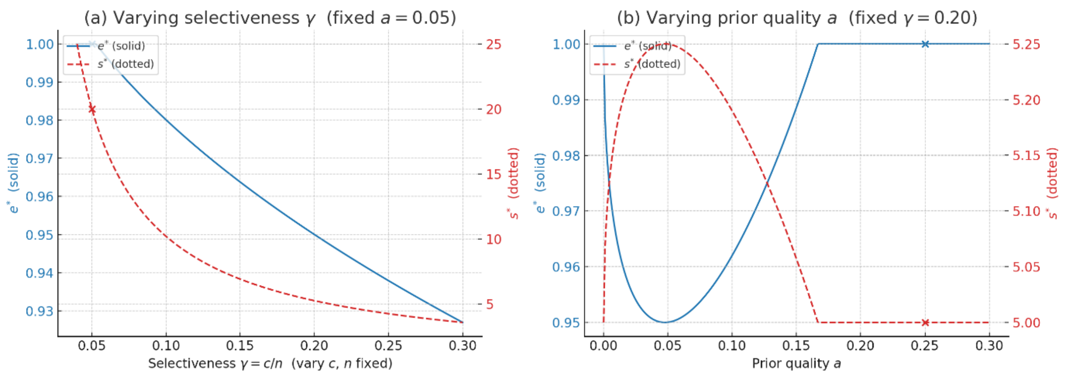

Figure 1: Numerical illustration of equilibrium behaviour of accelerator e^* and s^* with (a) varying selectiveness γ and (b) varying prior quality of applicants a

4. Discussion

This paper introduces a formal model examining how start-up accelerators strategically allocate limited resources between pre-entry screening, which influences perceived cohort quality via signalling effects, and post-entry support, which directly enhances the quality of selected ventures. While these two dimensions compete for budgetary resources, they jointly shape overall cohort outcomes. Importantly, the equilibrium accelerator design emerges endogenously, influenced by environmental factors such as accelerator selectiveness and the underlying quality distribution of applicants. This approach provides a theoretical foundation to help explain empirical variations observed in accelerator designs and effectiveness.

By endogenizing accelerator design decisions, this study contributes to the theoretical accelerator literature by explaining how context-specific strategic choices can account for observed differences in practice and outcomes. For example, accelerators operating in environments characterized by predominantly lower-quality ventures may optimally choose to limit their screening efforts, reallocating resources instead toward enhanced post-entry support. In contrast, programs situated within ecosystems with stronger applicant pools and higher selectiveness may achieve greater effectiveness by prioritizing rigorous screening. Thus, variations in observed accelerator characteristics and outcomes may reflect rational strategic adaptation rather than implementation inconsistencies or suboptimal practices. These findings underline the importance of incorporating strategic determinants of accelerator design into future evaluations of their effectiveness, also in the interpretation of empirical results.

From a managerial perspective, the model highlights the importance of adapting accelerator design to the specific characteristics of the operating environment. Rather than identifying a single best-practice configuration, the findings suggest that the optimal allocation between pre-entry screening and post-entry support is contingent on contextual parameters and may shift over time. For instance, in settings where the applicant pool contains relatively few high-quality ventures—such as nascent entrepreneurial ecosystems or newly launched accelerators—greater emphasis on post-entry support may be warranted to build capabilities among selected start-ups. Conversely, when application numbers increase and the program becomes more selective, the marginal value of each cohort slot rises, potentially justifying more intensive investment in pre-entry screening per applicant. These insights underscore the value of a flexible, responsive design approach in accelerator management, aligned with shifts in applicant quality, program maturity, and ecosystem development.

Naturally, this study is subject to limitations arising from model simplifications. To explore these limitations, it is important to complement this research with further theoretical and empirical research. On the theoretical side, incentives of accelerators could be explored in a variety of settings. The accelerator's objective function could be modified to reflect a broader set of strategic goals, such as prioritizing improvements in lower-quality ventures for ecosystem-building accelerators or emphasizing relative rather than absolute improvements in quality for impact-oriented programs. Additionally, explicitly modelling downstream consequences of accelerator decisions—such as investor reactions, financing outcomes, or venture growth trajectories—would provide greater realism. Further research could also examine competitive dynamics among accelerators, endogenous application decisions by entrepreneurs, and reputational effects to illuminate how strategic accelerator design evolves within realistic entrepreneurial ecosystems. Finally, endogenizing additional critical design parameters, such as cohort size, could enhance our understanding of why accelerators differ significantly in their selectivity and how scale interacts strategically with screening and support decisions.

Empirical testing of the comparative static predictions developed here presents another promising direction for future research. Matched datasets linking accelerator decisions, applicant pool characteristics, and subsequent venture outcomes could empirically validate the theoretical propositions advanced in this paper. Such empirical investigations would strengthen the theoretical model's relevance and provide further managerial and policy guidance, clarifying how context-specific strategic resource allocations shape accelerator effectiveness.

Collectively, pursuing these theoretical and empirical avenues can advance scholarly understanding of accelerator strategies, providing deeper insights into the internal trade-offs and external constraints that shape entrepreneurship support organisations.

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Ethics Declaration

No ethical declaration needed for this paper.

AI Declaration

This manuscript benefited from AI-assisted copy editing using OpenAI's ChatGPT-4o. In this context, "AI-assisted copy editing" refers to AI-supported improvements to human-generated text for readability and style, and to ensure accuracy in grammar, spelling, punctuation, and tone. These improvements include wording and formatting changes, but did not involve generative editorial work or autonomous content creation.

References

Amezcua, A.S., Grimes, M.G., Bradley, S.W., Wiklund, J., 2013. Organizational sponsorship and founding environments: A contingency view on the survival of business-incubated firms, 1994-2007. Academy of Management Journal 56, 1628–1654. https://doi.org/10.5465/AMJ.2011.0652

Assenova, V.A., Amit, R., 2024. Poised for growth: Exploring the relationship between accelerator program design and start-up performance. Strategic Management Journal 45, 1029–1060. https://doi.org/10.1002/SMJ.3581

Avnimelech, G., Dushnitsky, G., Ellsaesser, F., Fitza, M., 2024. Are accelerators akin to breweries or wineries? A Bayesian variance decomposition of accelerator and cohort effects. Strategic Management Journal. https://doi.org/10.1002/SMJ.3665

Bergman, B.J., McMullen, J.S., 2022. Helping Entrepreneurs Help Themselves: A Review and Relational Research Agenda on Entrepreneurial Support Organizations. Entrepreneurship Theory and Practice 46, 688–728. https://doi.org/10.1177/10422587211028736

Chowdhury, F., Audretsch, D.B., Belitski, M., 2019. Institutions and Entrepreneurship Quality. Entrepreneurship: Theory and Practice 43, 51–81. https://doi.org/10.1177/1042258718780431/SUPPL_FILE/ONLINE_APPENDIX_FINAL.PDF

Cohen, S., Fehder, D.C., Hochberg, Y. V., Murray, F., 2019. The design of start-up accelerators. Res Policy 48, 1781–1797. https://doi.org/10.1016/J.RESPOL.2019.04.003

Cohen, S., Hochberg, Y. V., 2014. Accelerating Start-ups: The Seed Accelerator Phenomenon. SSRN Electronic Journal. 1. https://doi.org/10.2139/ssrn.2418000

Cusolito, A.P., Dautovic, E., McKenzie, D., 2021. Can Government Intervention Make Firms More Investment Ready? A Randomized Experiment in the Western Balkans. Rev Econ Stat 103, 428–442. https://doi.org/10.1162/REST_A_00882

Dealroom, 2025. Accelerator Data.

Gonzalez-Uribe, J., Leatherbee, M., 2018. The Effects of Business Accelerators on Venture Performance: Evidence from Start-Up Chile. Rev Financ Stud 31, 1566–1603. https://doi.org/10.1093/RFS/HHX103

Gonzalez-Uribe, J., Reyes, S., 2021. Identifying and boosting "Gazelles": Evidence from business accelerators. J financ econ 139, 260–287. https://doi.org/10.1016/J.JFINECO.2020.07.012

Hallen, B.L., Cohen, S., Bingham, C.B., 2020. Do Accelerators Work? If So, How? Organization Science 31, 245-–534. https://doi.org/https://doi.org/10.1287/orsc.2019.1304

Hallen, B.L., Cohen, S., Park, S.H., 2023. Are seed accelerators status springboards for start-ups? Or sand traps? Strategic Management Journal 44, 2060–2096. https://doi.org/10.1002/SMJ.3484

Lall, S.A., Chen, L.W., Roberts, P.W., 2020. Are we accelerating equity investment into impact-oriented ventures? World Dev 131, 104952. https://doi.org/10.1016/J.WORLDDEV.2020.104952

Yu, S., 2019. How Do Accelerators Impact the Performance of High-Technology Ventures? Manage Sci 66, 530–552. https://doi.org/10.1287/MNSC.2018.3256