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The role of entrepreneurial ecosystems for start-up acceleration in emerging markets

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Abstract

Start-ups are an important component of driving context-sensitive sustainable development in emerging markets based on domestic innovation. However, knowledge on how best to support the capabilities, networks and access to finance of such ventures is limited, specifically in emerging markets. In this paper, we leverage novel data from a pan-African start-up accelerator to understand whether and why accelerators are effective. Adopting an entrepreneurial ecosystem lens and conceptualizing accelerators as intermediaries within ecosystems, we test two competing views of accelerator effectiveness: substitution and complementarity. Our results provide support for a complementarity view, where the positive effects of accelerators are higher in more mature ecosystems. We contribute to the literature by drawing attention to the importance of the context within which accelerators are situated, challenging the predominant approach of substituting for missing ecosystem components in emerging markets.

Keywords: Accelerator, start-up, entrepreneurial ecosystem, entrepreneurship support, impact assessment

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Declaration of competing interests

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1 Introduction

Young high-growth firms can be key drivers of economic development, including job creation, context-sensitive innovation and growth (Audretsch et al., 2006; Haltiwanger et al., 2013). This is particularly important in emerging markets (EMs) where development needs are high and pressing. Yet, high-growth start-ups are particularly scarce in EMs, despite high overall entrepreneurship rates compared to high-income countries (HICs) (Eslava et al., 2022; Monitor, 2025). To address this gap more than 1,500 start-up accelerators have been established in EMs (Dealroom, 2024). Accelerators are cohort-based, time-bound programs that combine direct resource provision, capacity building and networking opportunities to support early-stage ventures to scale, in particular by enabling them to access finance (Cohen et al., 2019; Hallen et al., 2020; Woolley & MacGregor, 2022).

However, crucially, little is known about the effectiveness of accelerators in EMs. Evidence from exclusively or dominantly HIC contexts shows that accelerator participation is associated with increased investment, affiliation with higher-status investors and higher growth levels on average (Assenova & Amit, 2024; Hallen et al., 2023). The rapid diffusion of accelerators from Silicon Valley to EMs reflects an implicit expectation that these models can be successfully transplanted (Guerrero, 2021). Yet, entrepreneurial contexts in EMs differ substantially from their HIC counterparts. Entrepreneurial investment flows are significantly lower, interest rates are higher, local-currency finance is highly limited, and the wider support infrastructure is generally weaker (Assenova & Agarwal, 2025; Casanova et al., 2018; Stam et al., 2025). In addition, while these conditions apply to EMs on average, there is large and often underrepresented heterogeneity between EMs concerning the maturity and quality of their local business environment (Brown, 2022; Mulugetta et al., 2022). Indeed, the limited quantitative evidence from EMs paints an ambiguous picture of accelerator effectiveness. Contrary to HICs, recent studies in the context of the Western Balkans (Cusolito et al., 2021), Colombia (Gonzalez-Uribe & Leatherbee, 2018), and across multiple EMs (Lall et al., 2020) find inconsistent evidence of acceleration leading to higher revenue growth, but no impact on a start-up's ability to raise finance. Taken together, this emerging evidence raises a central puzzle: Do accelerators in EMs work? And if so, what drives the heterogeneous outcomes across accelerators in EMs?

To be able to address this puzzle, we adopt an entrepreneurial ecosystem (EE) lens. The existing focus of the literature on accelerators' internal design choices fails to explain our puzzle as program designs in EMs show no meaningful structural differences to their counterparts in HICs (Assenova & Amit, 2024; Lall et al., 2020; Roberts & Lall, 2019). Instead, we conceptualize accelerators as intermediaries embedded within the EE, defined as a set of interdependent actors and factors in a particular region that are governed to enable entrepreneurship (Spigel & Harrison, 2018; Stam, 2015). From this perspective, an accelerator's impact on a venture's ability to attract finance to scale is contingent not only on its internal design but also on the surrounding entrepreneurial ecosystem (Bade, 2026; Fehder, 2024; Goswami et al., 2018).

Theoretical predictions regarding this relationship, however, are conflicting. A "substitution" view, rooted in resource dependence theory, emphasizes accelerators as substitutes for missing resources and for inefficient institutions (Amezcua et al., 2013; Bade, 2026; Bischoff et al., 2020). According to this logic, accelerators buffer ventures from hostile environments through direct resource provision and bridge them to critical resources, implying that acceleration should yield the strongest gains for ventures where ecosystem gaps are largest, that is, in less mature ecosystems. On the other hand, a "complementarity" perspective highlights accelerators as catalysts that orchestrate and intensify existing ecosystem linkages (Fehder, 2024; Qin, 2025). According to this logic, accelerators enhance ventures' capacity to absorb knowledge spillovers, mobilize networks, and convert certification into investment where ecosystems are already relatively munificent. Building on these divergent perspectives, we develop competing hypotheses regarding the ecosystem contingency of accelerator effectiveness in emerging markets. First, based on the substitution view, we hypothesize that accelerators have a higher impact on start-ups in less mature ecosystems. Second and by contrast, based on the complementarity view, we hypothesize the opposite, i.e., accelerators have a higher impact on start-ups in more mature ecosystems.

We empirically test these hypotheses by leveraging a novel dataset from the "Scaling Digital Agriculture Innovations through Start-ups" (SAIS) accelerator, a pan-African program supporting ventures across diverse entrepreneurial ecosystems. Between 2020 and 2023, the program supported 73 start-ups selected from a pool of 1,198 applicants. Empirically, we capture one critical, observable manifestation of subsequent start-up success, namely the realized access to growth finance measured as raising investment within 24 months after the program. We employ an Inverse Probability of Treatment Weighting (IPTW) approach to compare realized investment of accelerated start-ups against a counterfactual group of narrowly rejected applicants (Assenova & Amit, 2024; Hallen et al., 2020).

Our results provide strong support for the complementarity view. First, we find that, on average, the pan-African accelerator significantly increases a start-up's likelihood of raising investment. More importantly, we find that these effects are heterogeneous: start-ups operating in more mature entrepreneurial ecosystems derive significantly larger benefits from acceleration compared to those in less mature environments in terms of their likelihood of raising investment. Rather than acting as a substitute for missing markets and resources, the accelerator appears to function most effectively when it can leverage existing ecosystem assets. By contrast, in robustness checks, we do not observe a systematic ecosystem moderation for start-ups' ability to obtain grant funding or very large investments.

This study makes three main contributions. First, we provide novel quantitative evidence that accelerators can meaningfully support the access to growth financing of start-ups in EMs, challenging the skepticism arising from inconsistent prior results in other emerging markets. Second, we advance a complementarity view of acceleration in EMs by showing empirically that start-ups in mature EEs benefit more from acceleration than those in less mature EEs. This challenges the prevailing 'gap-filling' view of entrepreneurship support in emerging markets and carries clear managerial and policy implications: accelerators are not a one-size-fits-all solution across heterogeneous EEs in emerging markets. Third, we contribute to ongoing EE measurement debates providing an output-based proxy that captures ecosystem capacity to generate investable ventures.

2 Theory and hypotheses

2.1 The role of accelerators in supporting start-ups in emerging markets

2.1.1 The accelerator model in emerging markets

The accelerator model emerged in HICs and diffused to EMs. Early programs such as "Y-Combinator" and "Techstars" in the United States provided the template for accelerators in emerging markets, including "Katapult Africa", "Flat6Labs" and "54 Collective" next to a range of donor- and corporate-backed programs across Africa, Latin America, and South Asia (Lall et al., 2020; Roberts & Lall, 2019). Across HICs and EMs, accelerators share a common organizational structure. They are time-bound, cohort-based programs that select a small number of early-stage ventures from a large pool of applicants, provide structured training and capability building, offer individualized mentoring and coaching, and orchestrate peer interactions and curated exposure to external stakeholders such as business partners and investors (Avnimelech et al., 2025; Cohen et al., 2019; Hallen et al., 2020; Woolley & MacGregor, 2022). These features distinguish accelerators from other support models, especially incubators, which are typically property-based, of longer duration, and with less peer-to-peer programming (Bergman & McMullen, 2022). For the accelerator model, program design elements are well documented without meaningful structural geographical differences (Roberts & Lall, 2019): Selection mechanisms screen for growth-oriented ventures (Assenova, 2021; González-Uribe & Reyes, 2021); curricula and workshops structure learning (Assenova & Amit, 2024); one-to-one mentoring and coaching enable individualization (Assenova, 2020; Gonzalez-Uribe & Leatherbee, 2018; Rechter & Avnimelech, 2024); cohort formats and spatial arrangements shape peer collaboration (Avnimelech et al., 2025; Krishnan et al., 2021; Roche et al., 2024); and networking events and certification practices govern external linkages (Cai & Szeidl, 2018; Dushnitsky & Sarkar, 2022; Giudici et al., 2018; Hallen et al., 2020).

2.1.2 Challenges to scaling and financing start-ups in emerging markets

Although the accelerator template has diffused largely unchanged from HICs to EMs, the environments in which EM ventures operate differ systematically in terms of resource availability and institutional complexity. These contextual differences shape both the challenges of scaling and financing start-ups as well as the conditions under which accelerators can be effective.

On the resource side, start-ups in many EMs face scarcity of financial and non-financial resources critical for scaling and heightened information asymmetries about how to access these resources (Busch & Barkema, 2022; Cao & Shi, 2021). Markets for venture investments are often thin, with fewer private investors, weaker first-mover incentives, higher interest rates, limited local-currency finance and regulatory frameworks that complicate equity and debt transactions making access to growth financing a key constraint for scaling (Assenova & Agarwal, 2025; Bustamante et al., 2021; Casanova et al., 2018). Further, ventures are frequently geographically distant from key resource holders and must engage investors, donors, and partners located elsewhere (Rawhouser et al., 2024). Information asymmetries amplify these constraints, as entrepreneurs may lack clarity about who controls critical resources and how they can be accessed (Aldrich & Kim, 2007; Sydow et al., 2022).

Institutionally, EM ventures often operate in environments characterized by complex mixes of overlapping and sometimes conflicting institutional logics (Greenwood et al., 2011; Marquis & Raynard, 2015). Formal rules governing contracting, registration, and finance coexist with powerful informal institutions, such as identity-based networks, community norms, and kinship ties, that structure access to customers, labor, and capital (Khayesi & George, 2011; Khayesi et al., 2014; Sydow et al., 2022). Resource acquisition is frequently governed by the opaque interplay of these formal and informal institutions, creating uncertainty about which practices are legitimate for different audiences, especially when ventures simultaneously engage local communities and foreign investors (Field et al., 2025; Sydow et al., 2022).

In response, many EM ventures pursue scaling trajectories that differ from those in HICs: some integrate social and community goals more centrally into their business models, others internationalize early to circumvent local constraints, and many transition from informal to more formal organizational forms as they grow (Adomako et al., 2019; Sutter et al., 2017; Sydow et al., 2022). Taken together, resource scarcity, institutional complexity, and distinct venture trajectories imply that the challenges accelerators must address in EMs differ from those in HICs.

Importantly, these conditions are not uniform across EMs. Entrepreneurial ecosystems vary substantially in the depth of capital markets, density of support organizations, and quality of formal and informal institutions (Stam et al., 2025). This heterogeneity suggests that the effectiveness of accelerator mechanisms may be contingent on the surrounding environment.

2.1.3 The effectiveness of acceleration in emerging markets

Evidence on accelerator effectiveness from HICs and global samples suggests that participation in an accelerator is associated with higher growth, increased funding, and affiliation with higher-status investors (Assenova & Amit, 2024; Hallen et al., 2023). However, recent quantitative studies in EMs contexts yield more ambiguous findings. Evaluations from the Western Balkans and Colombia report that acceleration does not systematically increase equity fundraising and only yields inconsistent revenue effects (Cusolito et al., 2021; Gonzalez-Uribe & Leatherbee, 2018). A global evaluation of impact-oriented accelerators finds that acceleration boosts equity funding in HICs but not in EMs (Lall et al., 2020). These mixed results raise doubts about whether accelerator support translates into improved access to growth finance in EMs.

At the same time, related research on incubators and other organizational intermediaries in EMs shows that support organizations can help ventures overcome resource constraints and institutional frictions (Armanios et al., 2017; Dutt et al., 2015). Given that accelerators explicitly target investment readiness, network access, and certification, their core mechanisms are well aligned with the resource and information challenges EM ventures face. We therefore expect, on average, a positive effect of accelerator participation on ventures' access to growth finance. Formally:

Hypothesis 1 (H1). *Participation in an accelerator program increases a start-up's likelihood of securing investments in emerging markets.*

2.2 Ecosystem-contingency of acceleration across emerging markets

To explain heterogeneity in accelerators' effectiveness across EMs, we adopt an entrepreneurial ecosystem perspective, complementing the prevailing focus on internal program design (Assenova & Amit, 2024; Avnimelech et al., 2025; Cohen et al., 2019) and start-ups' prior capabilities (Chang & Assenova, 2026). We conceptualize accelerators as intermediaries embedded within entrepreneurial ecosystems, defined as spatially bounded configurations of interdependent actors, resources, and institutions that jointly enable productive entrepreneurship (Stam, 2015; Stam & van de Ven, 2021). From this perspective, an accelerator's impact on a start-up's ability to scale and obtain investments depends not only on its internal design but also on the maturity of the surrounding ecosystem (Dutt et al., 2015; Fehder, 2024; Goswami et al., 2018). We define an entrepreneurial ecosystem's maturity as its capacity to generate productive entrepreneurship, reflecting the extent to which resources, institutions, and actors are present and effectively interconnected (Bade, 2026; Leendertse et al., 2022; Stam & van de Ven, 2021).

A central challenge is that theory offers opposing expectations about where accelerators should be most effective in enabling access to growth finance for start-ups. On the one hand, accelerators may create the largest marginal benefits in less mature ecosystems, where resource and institutional complexity are greatest and their buffering and bridging roles are most needed. On the other hand, accelerators may be most effective in more mature ecosystems, where complementary resources, institutions, and networks allow accelerator mechanisms to be fully realized and translated into actual growth financing for start-ups. We formalize these competing expectations by contrasting a substitution view and a complementarity view.

2.2.1 Substitution view on ecosystem contingency

The substitution view builds on organizational sponsorship and resource dependence theory. Organizational sponsors help ventures overcome environmental constraints by buffering them from hostile conditions and bridging them to external resource holders (Amezcua et al., 2013; Flynn, 1993). Applied to accelerators in EMs, this view emphasizes their role as substitutes for missing or underdeveloped markets, resources and opaque institutional arrangements.

First, accelerators can buffer start-ups from resource-poor and institutionally complex environments by directly providing resources and capabilities (Amezcua et al., 2013). Structured training, intensive mentoring, and seed funding offer ventures a protected space to develop investment readiness without immediately relying on local market institutions, investors, or support services. This buffering role is particularly valuable in less mature ecosystems, where markets for entrepreneurial finance and support are thin, the number of potential resource holders is small, and information about where resources reside and how to access them is highly opaque. In such settings, accelerators can partially substitute for missing external services by directly supplying knowledge, relational guidance, and sometimes financial capital that would otherwise be unavailable (Gonzalez-Uribe & Leatherbee, 2018; McKenzie & Woodruff, 2014).

Second, accelerators can bridge start-ups to external stakeholders and provide institutional support that would, in more mature ecosystems, be mediated by established market and social structures (Amezcua et al., 2013; Bade, 2026; Baum & Oliver, 1991). Through networking events, demo days, and curated introductions, accelerators connect ventures to investors and partners with whom they lack pre-existing ties, thereby substituting for underdeveloped informal communities, professional networks and local institutions facilitating ties (Clingingsmith & Shane, 2018; Dushnitsky & Sarkar, 2022). Accelerator affiliation further acts as a certification signal that reduces information asymmetries about venture quality. This signaling role is expected to be particularly valuable in less mature ecosystems, where there is limited precedent for high-growth start-ups and where local investors may be less experienced in evaluating such ventures (Armanios et al., 2017; Plummer et al., 2015; Zimmerman & Zeitz, 2002). In addition, accelerators may engage in institutional work that helps establish or improve informal and formal market infrastructures, such as lobbying for standardized contracts or minority investor protections, thereby easing exchange between start-ups and external resource holders in contexts where such infrastructure is missing or weak (Dutt et al., 2015; Lawrence & Suddaby, 2006; Zietsma & Lawrence, 2010).

From this substitution perspective, ecosystem maturity moderates accelerator effectiveness in a specific way. In less mature ecosystems, where resource scarcity, institutional complexity, and network gaps are most severe, the buffering and bridging roles of accelerators are potentially most consequential: by substituting for missing markets and institutions, accelerators can yield substantial improvements in ventures' access to investment. In more mature ecosystems, by contrast, many of these functions are already provided by other actors and institutions, so the marginal contribution of accelerators to start-ups' scaling trajectories is more limited. Accordingly, the substitution view predicts:

Hypothesis 2a (H2a). *The positive effect of accelerator participation on start-ups' likelihood to secure investment is larger in less mature entrepreneurial ecosystems than in more mature ecosystems.*

2.2.2 Complementarity view on ecosystem contingency

The complementarity view starts from a relational understanding of accelerators as ecosystem intermediaries whose value creation depends on and amplifies pre-existing ecosystem structures and actors (Bergman & McMullen, 2022; Fehder, 2024). Rather than primarily substituting for missing resources and institutions, accelerators orchestrate and intensify linkages between ventures and other ecosystem actors. From this perspective, ecosystem maturity enhances the effectiveness of the same core mechanisms of capability-building, peer-to-peer learning, and network access.

First, the quality and relevance of mentoring, coaching, and curricula depend on the availability of experienced entrepreneurs, domain experts, and investors who can serve as mentors and external speakers. In more mature ecosystems, accelerators can draw on a larger and more diverse pool of high-quality mentors with deep local and sector-specific knowledge, improving the fit between advice and ventures' strategic and financing challenges (Assenova, 2020; Rechter & Avnimelech, 2024). Where ecosystems are less mature and the pool of experienced mentors is small, accelerators face structural limits in tailoring high-quality, context-specific capability-building.

Second, peer mechanisms are also shaped by ecosystem maturity. In more mature ecosystems, deeper applicant pools enable more selective admission, producing cohorts with stronger prior experience, richer knowledge bases, and higher growth ambitions (Avnimelech et al., 2025; Gonzalez-Uribe & Leatherbee, 2018). These stronger cohorts foster more intensive peer-to-peer learning, collaboration, and benchmarking within accelerators, thereby enhancing ventures' ability to identify and pursue growth finance opportunities (Krishnan et al., 2021). In less mature ecosystems, by contrast, cohort composition may be less competitive and more heterogeneous or geographically dispersed, weakening peer effects and limiting the extent to which accelerators can generate dense intra-cohort ties (Avnimelech et al., 2025; Chang & Assenova, 2026; Roche et al., 2024).

Third, ecosystem maturity shapes the power of accelerators' networking and signaling functions. In more mature ecosystems, a larger number and greater diversity of investors and partners increases the likelihood that curated introductions result in good matches and actual transactions (Dushnitsky & Sarkar, 2022; Giudici et al., 2018). Signaling through accelerator affiliation is also more valuable when there are many potential recipients who can act upon the signal and when formal and informal institutions reduce transaction costs, making it easier to convert interest into investment (Bafera & Kleinert, 2023; Hallen, 2008). By contrast, in less mature ecosystems, even well-prepared ventures may struggle to translate enhanced visibility and certification into investments if there are few active investors, weak contractual protections, or high transaction costs. Given the typically short duration of accelerator programs, their ability to build such market infrastructure from scratch is limited; instead, they rely on the pre-existence of complementary institutions and resource holders. On top of this, accelerator activities may generate ecosystem-wide spillovers as investors and other actors engage with accelerated ventures, diffusing practices and deepening inter-organizational ties (Giudici et al., 2018; Goswami et al., 2018). These spillovers are more likely to materialize and feed back into additional resource flows in ecosystems where networks are already dense and actors are accustomed to exploratory collaboration

(Fehder, 2024).

From this complementarity perspective, accelerators create the largest marginal impact on ventures' ability to secure investments for growth when embedded in ecosystems that already provide a critical mass of resources, supportive institutions, and networked actors. In less mature ecosystems, by contrast, the absence of such complementarities constrains the extent to which accelerators can improve capabilities, visibility, and networking and the extent to which improvements can be converted into actual investments. Accordingly, the complementarity view yields a prediction opposite to the substitution view:

Hypothesis 2b (H2b). *The positive effect of accelerator participation on start-ups' likelihood to secure investments is larger in more mature entrepreneurial ecosystems than in less mature ecosystems.*

3 Research methods

3.1 Research setting and sample

To empirically test our hypotheses, we draw on data from the accelerator "Scaling Digital Agriculture Innovations through Start-ups" (SAIS) which supports early-stage ventures to raise investment for growth. The accelerator exclusively targets start-ups which are registered and operate in African countries, with a focus on the agriculture and food sectors. The primary aim of the program is to enhance the "investment readiness" of start-ups through customized and intensive consulting services, as well as by facilitating connections with potential investors, business partners, and customers over the course of one year. This investment orientation seeks to address the ongoing challenge of low investment levels experienced by start-ups in Africa. Funded by the German Ministry for Economic Cooperation and Development, co-financed by the Bill & Melinda Gates Foundation, and implemented by the German development agency GIZ, the accelerator ultimately aims to scale innovative solutions that improve agricultural productivity, enhance farmers' incomes, and foster climate adaptation in the agricultural sector. Notable participants include "Koolboks", a Nigerian firm providing solar-powered cooling solutions to mitigate post-harvest losses; "Hello Tractor", a Kenyan venture leveraging IoT technology to optimize farm equipment management; and "Jabu Logistics", a start-up from Namibia specializing in last-mile logistics and food distribution across Southern Africa.

Each SAIS cohort accommodates 20 to 24 start-ups annually which are selected from over 300 applicants in a 3-step process consisting of eligibility-review, pre-selection of written application by a jury and, finally, interview-based selection. Further details on the selection process are given in the supplementary materials.

Selected start-ups undergo a comprehensive program designed to build firm capabilities through personalized coaching, networking, and certification over the course of one year. Upon admission, each start-up collaborates with SAIS staff and external experts to develop a customized company development plan that targets specific improvements aimed at enhancing investment readiness. These improvements may include refining product-market fit, go-to-market strategies, investor presentations, and financial data management. Weekly virtual coaching sessions with dedicated experts assist start-ups in executing these strategies. Additionally, start-ups may receive customized support packages that can reach a value of up to EUR 50,000 including external professional services, procurement assistance, and digital agency services. Further, SAIS collaborates with "Melanin Kapital", a fintech platform providing financing solutions to small-medium businesses in Africa, through which start-ups can access working capital loans of up to EUR 50,000. The loan is repayable over nine months at a 1.5% annual interest rate, supporting start-ups in managing their cash flow. Networking opportunities with investors and potential partners are available through in-person events, culminating in a demo day pitch at the conclusion of the one-year program. Monthly virtual exchanges further facilitate peer-to-peer learning among participants. Certification and increased visibility for participants are provided through presentations at stakeholder events, digital presence on the various online platforms of SAIS, and recognition of participation on investor platforms such as Dealroom and PitchBook.

For this study, we analyze the SAIS cohorts from 2020 to 2023. In total, 1,198 start-ups applied, with 335 (28%) meeting the eligibility criteria, e.g., having existing minimum viable product and aiming to raise funding for growth. In practice, many applications were either incomplete or submitted by start-ups at the ideation stage, which lacked a launched product or sufficient customer traction. In the second stage, a jury scored the written applications of these start-ups, with 135 (11% of the total applicants) subsequently invited for further interviews. In the third stage, 73 start-ups (6% of the total applicants) were selected based on interview scores and subsequent discussions among the SAIS team. To limit the sample to comparable start-ups (see also the discussion on selection bias in our methodology section), we focus on the start-ups that were invited for interviews for the cohorts 2020 to 2023. Two start-ups (one selected, one rejected) are excluded from the analysis due to incomplete application records, resulting in a final sample of 133 start-ups.

3.2 Variables and measures

3.2.1 Independent and dependent variables

For our study, the main independent variable is an indicator for participation in the SAIS accelerator. Conceptually, we study ventures' access to external growth finance. Empirically, we operationalize this construct using realized financing outcomes. Our main dependent variable, investment, is a binary indicator equal to 1 if the start-up raises any external equity or debt financing within 2 years after the accelerator program ends (0 otherwise). In robustness analyses, we examine investment USD 100,000, indicating whether the start-up raises more than USD 100,000 in external equity or debt financing within the same window; Grant, indicating whether the start-up receives any grant funding within 2 years after program end; and Operational, an indicator for whether the start-up remains operational as of October 2024. All indicators do not include any financing provided by the accelerator, e.g., the working capital loans. In the supplementary materials, we also analyze the impact of acceleration on the amount of investments and grants raised within 2 years after program end. To derive the outcome measures for investment and grants, we hand-collected publicly available funding data for each start-up in our sample. In detail, we use funding data from *Dealroom* and supplement it with additional deals identified in various sources for African start-up funding, including *Crunchbase*, *Briter*, *Africa - The Big Deal*, as well as the start-ups' webpages and press coverage. This multi-source strategy seeks to reduce the likelihood of overlooking funding information due to incomplete coverage of early-stage deal data in Africa by any single source. Start-up survival was assessed manually based on evidence of recent operational activity online as of October 2024, e.g., updated websites, recent social media posts or press coverage.

3.2.2 Moderator variable

We define the maturity of a start-up's entrepreneurial ecosystem as the capacity of an ecosystem to generate productive entrepreneurship (Spigel & Harrison, 2018). Consequently, we operationalize ecosystem maturity using a measure of ecosystem output (Bade, 2026; Stam & van de Ven, 2021): the number of start-ups securing external funding greater than USD 10,000 within a country in the 10 years prior to the focal start-up's application. Figure 1 illustrates this measure for the example 2015-2024 period. Using funded start-ups as an ecosystem output proxy aims to capture the maturity of the joint configuration of the underlying ecosystem elements that are particularly relevant for ventures seeking growth finance, rather than broader measures such as overall business registrations.

We operationalize ecosystem maturity in this way for three reasons. First, early ecosystem measurement often emphasizes individual ecosystem components but offers limited theoretical and empirical guidance on how these components interact to jointly produce productive entrepreneurship (Hess et al., 2025; Leendertse et al., 2022). We therefore use an output-based proxy that captures the revealed capacity of the ecosystem as a system (Bade, 2026). Second, consistent cross-country data on many ecosystem components are not available for our full sample (e.g., Stam et al. (2025) cover only parts of it), whereas start-up funding events are comparatively well documented across Africa due to specialized data providers. Third, start-up activity in African countries is typically concentrated in the capitals (Field et al., 2025) aligning our national measurement of maturity with the prevailing regional definition of entrepreneurial ecosystems (Stam, 2015). In addition, several critical elements contributing to ecosystem maturity are at the national-level such as institutional configurations (Ács et al., 2014).

3.2.3 Covariates

Following the prior literature on the role of venture and founder characteristics for a start-up's performance (Eddleston et al., 2016), we use various measures of these characteristics at the time of application as controls. These measures include a start-up's revenue (in millions USD), its volume of funding (in millions USD), two binary indicators of a start-up's investment and grant status that indicate whether the start-up has raised any investment or grants respectively prior to the application, the company's age (measured in years since incorporation), and the start-up's activity across segments of the agricultural value chain

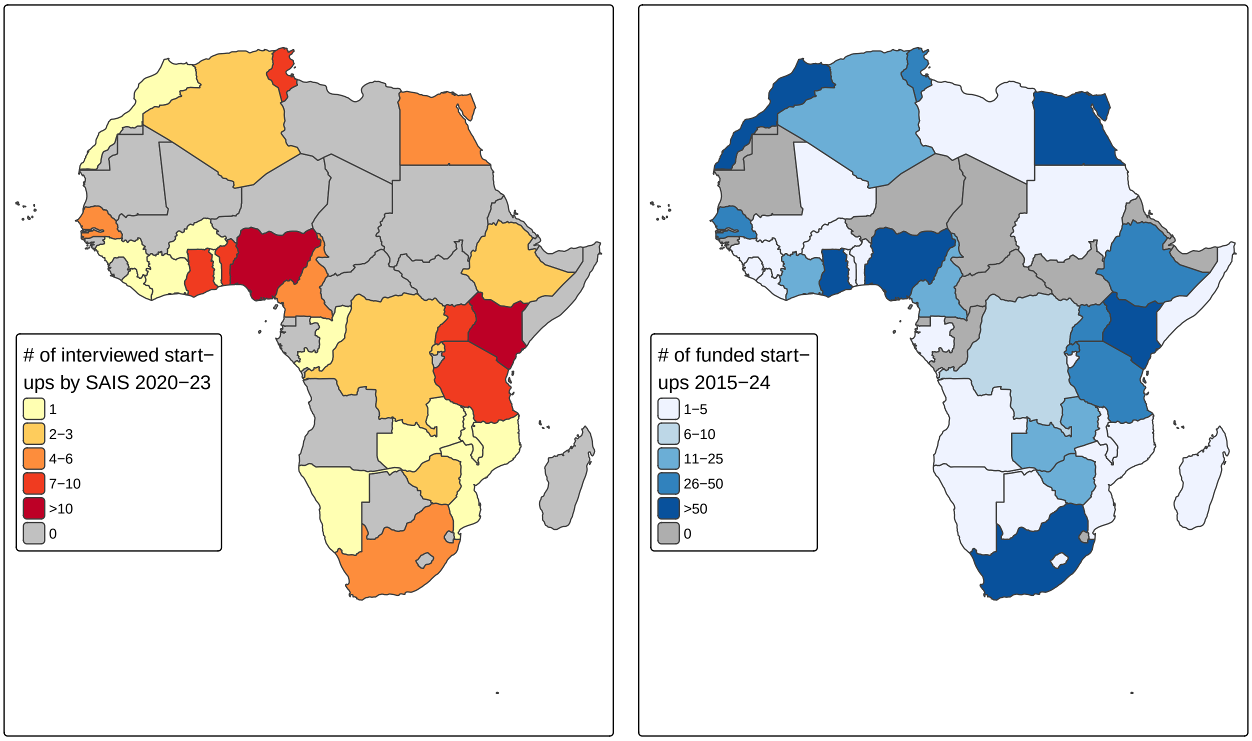

Figure 1: Country-level distribution of start-ups in sample (left-side) and ecosystem maturity as measured by the number of start-ups having raised more than USD 10,000 between 2015 and 2024, by country, sourced from Dealroom (right-side)

(such as inputs, production, post-harvest, logistics, finance, planning, farmer expertise). Importantly, we use detailed start-up assessments from the SAIS jury's scoring that reflect the quality of the founding team, the business model, the size of the market opportunity, and further relevant indicators to predict a start-up's potential (further details on the scoring are provided in the supplementary materials). This scoring allows us to account for additional start-up characteristics that are seldom available in multi-accelerator studies (Fehder, 2024; Gonzalez-Uribe & Leatherbee, 2018; González-Uribe & Reyes, 2021). Finally, we include cohort and year indicators (with 2020 as the baseline), language indicators (French-speaking vs. English-speaking, with English-speaking set as the baseline) as well as country dummies. The country distribution of the sample is depicted in Figure 1. In the supplementary materials, we show all summary variables separately for start-ups that were rejected and for those that participated in the accelerator including their country distribution. All controls are derived from the records of the accelerator's application data, except for the funding data, which is from *Dealroom*.

3.2.4 Summary statistics

An overview of the descriptive statistics of all variables from our sample is presented in Table 1. The table illustrates that interviewed start-ups in our sample were typically revenue-generating (median revenue USD 60,000, mean USD 270,000), had incorporated around three years prior to the application, and partially had raised investment (23%) and grants (20%) at this point. This profile reflects the program's strategic focus on scaling existing ventures through obtaining external investments rather than developing start-up ideas. Further, the descriptive statistics for the selected start-ups show that on average the SAIS team selected start-ups with higher pre-acceleration revenue, investment, and higher application scoring. This indicates that the accelerator aims to select promising start-ups resulting in non-randomized treatment selection, a feature commonly observed in accelerators (Gonzalez-Uribe & Leatherbee, 2018; Hallen et al., 2020). A detailed comparison of selected and rejected start-ups is presented in the supplementary materials.

3.3 Empirical strategy

3.3.1 Design and identification

We evaluate the impact of accelerator participation on start-up's realized investment by analyzing the sample of 133 start-ups that advanced to the interview stage of the SAIS accelerator program across cohorts from 2020 to 2023. Our analysis employs a rigorous comparative approach, with the treatment group consisting of the 72 start-ups that were subsequently selected for participation in the accelerator program. The counterfactual group consists of 61 start-ups that were also interviewed but ultimately not selected for participation. Both groups represent high-quality start-ups, as they have satisfied the accelerator's initial eligibility criteria and successfully passed preliminary jury evaluations.

Our empirical strategy focuses on estimating the average effect of accelerator participation on start-ups' likelihood of raising growth finance post-accelerator participation. Specifically, we compare treated start-ups (participants) and untreated control start-ups (rejected interviewees) in their ability to obtain an investment (including equity and debt). We employ an Inverse Probability of Treatment Weighting (IPTW) methodology (Hirano et al., 2003; Rosenbaum & Rubin, 1983), an established econometric approach frequently applied in the accelerator evaluation literature (Assenova & Amit, 2024; Hallen et al., 2020).

Table 1: Sample description

Section	Variable	Sample (n=133) Mean	Min	Max	SD	Selected (n=72) Mean	SD
Independent var	Accelerator participation	0.54	0.00	1.00	0.50	1.00	0.00
Dependent var	Raised investment post acceleration	0.20	0.00	1.00	0.40	0.28	0.45
	Raised investment >$100k post acceleration	0.12	0.00	1.00	0.33	0.18	0.39
	Raised grant post acceleration	0.14	0.00	1.00	0.34	0.18	0.39
	Operational post acceleration	0.89	0.00	1.00	0.31	0.93	0.26
Start-up var	Application score	0.51	0.00	0.82	0.17	0.59	0.11
	Revenue in $mn	0.27	0.00	5.00	0.70	0.32	0.73
	ln(Revenue in $)	10.52	0.00	15.42	2.77	10.76	2.85
	Company age	3.35	0.03	16.26	2.51	3.41	2.56
	Raised invest pre acceleration	0.23	0.00	1.00	0.42	0.26	0.44
	Raised grant pre acceleration	0.20	0.00	1.00	0.40	0.22	0.42
	Invest amount pre acceleration in $mn	0.14	0.00	4.70	0.59	0.23	0.75
	ln(Invest amount pre acceleration in $)	1.90	0.00	15.36	4.58	2.38	5.16
	Grant amount pre acceleration in $mn	0.02	0.00	1.35	0.12	0.03	0.17
	ln(Grant amount pre acceleration in $)	1.46	0.00	14.12	3.74	1.71	4.09
	Value chain: Inputs	0.08	0.00	1.00	0.28	0.08	0.28
	Value chain: Production	0.26	0.00	1.00	0.44	0.28	0.45
	Value chain: Post-Harvest	0.17	0.00	1.00	0.38	0.19	0.40
	Value chain: Logistics/Consumption	0.45	0.00	1.00	0.50	0.44	0.50
	Value chain: Finance	0.30	0.00	1.00	0.46	0.29	0.46
	Value chain: Planning	0.23	0.00	1.00	0.42	0.25	0.44
	Value chain: Farmer education	0.16	0.00	1.00	0.37	0.17	0.38
Ecosystem var	No. funded start-ups	172.56	0.00	453.00	169.93	183.42	171.98
	ln(No. funded start-ups)	4.25	0.00	6.12	1.65	4.43	1.52
	No. funded agri-start-ups	16.24	0.00	41.00	15.28	17.36	15.76
	ln(No. funded agri-start-ups)	2.15	0.00	3.74	1.38	2.26	1.33
Cohort var	Cohort French	0.20	0.00	1.00	0.40	0.14	0.35
	Cohort 2021	0.17	0.00	1.00	0.38	0.19	0.40
	Cohort 2022	0.32	0.00	1.00	0.47	0.33	0.47
	Cohort 2023	0.32	0.00	1.00	0.47	0.31	0.46

IPTW enables the estimation of the average causal impact of accelerator participation by reweighting observations to create a pseudo-population in which treatment assignment is independent of measured baseline covariates under the assumption that observable characteristics capture the structural differences between treatment and control groups (Austin & Stuart, 2015). Note that our data does not allow identification using a regression discontinuity approach similar to Fehder (2024) and Gonzalez-Uribe and Leatherbee (2018), as the selection probability as a function of the application score does not feature discontinuities. This likely arises from the fact that the selection decision is informed by the scoring but is also based on a wider discussion among the jury.

3.3.2 IPTW estimation and main specifications

Our implementation of the IPTW approach consists of three main steps. First, we estimate a propensity score p_i for each start-up i, which reflects the probability of being selected into the accelerator program given its observed pre-program characteristics. Second, we assign each observation a weight: participating start-ups receive a weight of $1/p_i$, and non-participants receive a weight of $1/(1-p_i)$ (Hirano et al., 2003). Third, we estimate the average treatment effect of accelerator participation on start-up performance using a weighted binomial model with robust standard errors.

In greater detail, the propensity scores are estimated using the Covariate Balancing Propensity Score (CBPS) method developed by Imai and Ratkovic (2014), which directly incorporates covariate balance conditions into the estimation process. Compared to conventional approaches such as logistic regression, the CBPS improves covariate balance between treated and control units and is more robust to model misspecifications. The set of covariates used in the CBPS estimation aligns with those included in the outcome model (Stuart, 2010). These covariates include the start-up characteristics from the application process (e.g., revenue, investments, grants, age), jury scores of the application, the measure of ecosystem maturity, and cohort indicators. Following the weighting procedure, we assess covariate balance using both graphical diagnostics and quantitative metrics, as recommended by (Austin & Stuart, 2015), to ensure comparability between treated and control groups.

Finally, to test Hypothesis 1, we estimate the following equation using the weighted sample[1]:

$$\begin{aligned}\operatorname{logit}\big[P(Y_i = 1 \mid X_i)\big] = \beta_0 + \beta_1\, \mathit{AcceleratorParticipation}_i + \beta_2^{\top}\, \mathrm{X}_i \\ + \sum_{m=1}^{M} \gamma_m\, \mathit{Country}_{im} + \sum_{n=1}^{N} \delta_n\, \mathit{Cohort}_{in}.\end{aligned} \quad (1)$$

[1]The logit link is defined as $\operatorname{logit}(p) = \log\big[\frac{p}{1-p}\big]$.

Here, Y_i is the binary indicator of having raised investment two years after the SAIS program for start-up i, and in subsequent robustness analysis one of the three alternative binary dependent variables (investment larger than USD 100,000, having raised grant financing, and remaining operational). X_i collects all covariates at the time of application, namely the application score, the log of revenue, the start-up's age, indicators of prior investment and prior grant financing and the log of the ecosystem maturity measure. Further, the model includes dummies for the ten countries that have the largest number of observations M and for each accelerator cohort N; the cohort 2020 and the indicator of an English language cohort are omitted in N as those are the respective year and language baselines to avoid perfect multicollinearity.

For Hypothesis 2, we augment the above empirical specification by incorporating an interaction term between the indicator of accelerator participation and the ecosystem maturity measure (the log of the number of funded start-ups in the start-up's national ecosystem in the last decade). This interaction term allows for an exploration of how the maturity of the entrepreneurial ecosystem moderates the effects of accelerator participation on start-ups' realized access to growth finance. To estimate this equation, we use the same IPTW approach as described above. Here, the interaction term is only included in the outcome estimation, because it builds on the participation variable which is our dependent variable in the initial propensity score estimation. Hence, sample weights are identical to the estimations for H1 as we use the same set of covariates.

3.3.3 Robustness and validity checks

To examine the robustness of our results, we conduct various additional analyses for H1 and H2. First, we reestimate our IPTW approach using a trimmed sample instead of the full sample, excluding observations with propensity scores above 98% and below 2%, to test the robustness to the influence of extreme weights and improve the stability of the estimator (Imbens, 2015).

Second, we assess the stability of our findings by applying alternative weighting methods within the IPTW approach. Instead of utilizing the CBPS employed in the baseline, we first estimate propensity scores using a logit model.

Third, we incorporate alternative sets of covariates into our IPTW approach, both for estimating the propensity score and for the subsequent outcome model. Specifically, we replace country-fixed effects with a set of dummy variables indicating a start-up's position along the agricultural value chain. To mitigate the risk of overfitting, we include either country dummies or value chain indicators, but not both. Further, in a separate specification, we examine an alternative measure of entrepreneurial ecosystem maturity. In particular, we substitute the total number of funded start-ups in a country with a more focused measure: the number of funded start-ups specifically in the agricultural sector in that country over the past decade. This adjustment is motivated by the understanding that funding success for agricultural start-ups may differ systematically from that of other sectors due to structural features such as the relative size of the agriculture sector, geographic dispersion of actors (particularly in rural areas), limited sectoral digitization, and fragmented land ownership within the respective country (Barrett et al., 2017).

Fourth, to assess the potential risk of violations of the unconfoundedness assumption in our identification strategy, we conduct a pseudo outcome analysis (Imbens, 2015). Additionally, following (Weele & Ding, 2017), we assess sensitivity to unmeasured confounding by computing E-values for the odds ratios from our logistic regression estimates and corresponding confidence limits.

Finally, given the sample size of 133 observations, we assess the statistical power of our tests following the framework proposed by (Gelman & Carlin, 2014). In addition to examining power, we also investigate two related risks: (i) the probability of a sign error, which refers to obtaining a statistically significant coefficient with the incorrect sign, and (ii) the potential for the exaggeration of effect sizes among statistically significant estimates.

In the supplementary materials, we provide further details on the analyses of pseudo outcomes, sensitivity to unmeasured confounding and power.

4 Results

4.1 Results for Hypothesis 1: Impact of accelerator participation

Hypothesis 1 predicts a positive relationship between accelerator participation and start-ups realized access to growth finance in emerging markets. Our results, presented in Table 2, provide evidence supporting this hypothesis.

Specifically, we find that accelerator participation leads to an average increase in the log-odds of raising investment two years after the program, statistically significant at the 5%

Table 2: Estimated effects of accelerator participation on start-up investment (H1 baseline)

	Main DV	*Alternative DVs for robustness*		
	Investment	Investment>$100k	Grant	Operational
	(1)	(2)	(3)	(4)
Accelerator participation	1.31^{**}	1.51^{*}	1.26^{*}	3.93^{**}
	(0.65)	(0.79)	(0.65)	(1.73)
Application score	−1.39	2.88	1.39	−1.73
	(2.02)	(7.72)	(2.05)	(3.57)
ln(Revenue in $)	0.23	0.33	0.06	0.29
	(0.27)	(0.66)	(0.11)	(0.18)
Company age	−0.24	0.11	−0.22	0.45
	(0.15)	(0.15)	(0.20)	(0.41)
Raised invest pre acceleration	3.21^{***}	1.45	−0.60	4.48^{**}
	(0.86)	(0.99)	(0.86)	(2.02)
Raised grant pre acceleration	1.48	0.91	0.06	−1.66
	(0.90)	(1.15)	(0.83)	(1.04)
ln(No. funded start-ups)	0.37	−0.10	−0.34	0.34
	(0.34)	(0.33)	(0.36)	(0.31)
Intercept	−3.49	−10.43	−3.59	-4.27^{**}
	(3.14)	(6.95)	(2.46)	(1.95)
Country & cohort dummies	Yes	Yes	Yes	Yes
Observations	133	133	133	133

Note: ln(No. funded start-ups) is the ecosystem maturity measure (log of the number of funded start-ups in the last decade in a start-up's country). Coefficients for estimation of equation (1). Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

level. For our alternative dependent variables, we find further evidence that accelerator participation increases the log-odds of (2) raising investment exceeding USD 100,000 within two years, (3) obtaining grant financing and (4) remaining operational. The effects are statistically significant at the 10% and 5% level respectively.

To aid interpretation, Table 3 translates the estimated log-odds coefficients for accelerator participation into changes in predicted probabilities. Specifically, we use the observed mean outcome among rejected start-ups as the baseline probability (p_0), and calculate the corresponding post-treatment probability (p_1) by applying the estimated logit coefficient. This allows us to express treatment effects in terms of absolute probability changes.

The resulting magnitudes indicate that the effects of accelerator participation are economically meaningful. The estimated log-odds increase of 1.31 for the likelihood of raising investment translates into a probability increase from 11% to 32%, holding all else constant. We emphasize that these transformations depend on the chosen baseline probability, and due to the nonlinearity of the logit function, marginal effects vary across the distribution. The values shown are therefore illustrative and correspond to a representative case at the sample mean of the control group.

Table 3: Effect of accelerator participation on start-up investment (H1): Translation of log-odds into probabilities

	Main DV	*Alternative DVs for robustness*		
	Investment (1)	Investment>$100k (2)	Grant (3)	Operational (4)
Baseline probability, p_0	0.11	0.05	0.08	0.85
Baseline odds, o_0	0.13	0.05	0.09	5.78
Acceleration coefficient (log-odds), $\hat{\beta}_{\text{accel}}$	1.31	1.51	1.26	3.93
Acceleration odds ratio, $\exp(\hat{\beta}_{\text{accel}})$	3.71	4.53	3.53	50.97
Resulting odds with acceleration, o_1	0.48	0.23	0.32	294.48
Resulting probability with acceleration, p_1	0.32	0.19	0.24	1.00

Note: p_0 = baseline probability (observed mean success rate among start-ups that did not participate in the accelerator). $o_0 = p_0/(1-p_0)$ = corresponding baseline odds. $\hat{\beta}_{\text{accel}}$ = estimated log-odds coefficient for accelerator participation from the baseline logit model. $\exp(\hat{\beta}_{\text{accel}})$ = odds ratio associated with accelerator participation. $o_1 = o_0 \times \exp(\hat{\beta}_{\text{accel}})$ = resulting odds with accelerator participation. $p_1 = o_1/(1+o_1)$ = resulting probability with accelerator participation.

Next to increasing the likelihood of raising an investment, we also show that participating in the accelerator on average leads to an increase in the amount of investment raised by +192% within two years after the program. The effect is statistically significant at the 5% level and robust to alternative model specifications and estimations. The analysis for funding amount as outcome is reported in the supplementary materials.

4.2 Robustness of results for Hypothesis 1

In the following, we present evidence indicating that the identified positive effects of accelerator participation on a start-up's ability to raise investment remains predominantly robust despite alterations in our approach.

Identification of accelerator effects in our approach critically relies on successful reweighting of the sample. Using various diagnostics, we verify in the supplementary materials that our IPTW approach results in balanced covariate distributions of selected and rejected start-ups in the weighted sample facilitating a consistent estimation of the treatment effect of accelerator participation, assuming the condition of unconfoundedness (Austin & Stuart, 2015). Furthermore, to verify the robustness of our IPTW procedure, we reestimate using alternative specifications. The resulting coefficients and robust standard errors for the effect of participating in the accelerator are presented in Table 4.

Table 4: Robustness of estimated effects of accelerator participation on start-up investment (H1)

	Main DV	*Alternative DVs for robustness*		
Specification	Investment (1)	Investment>$100k (2)	Grant (3)	Operational (4)
Baseline	1.31** (0.65)	1.51* (0.79)	1.26* (0.65)	3.93** (1.73)
Trimmed sample	1.27* (0.70)	1.73 (1.63)	1.17* (0.63)	3.74** (1.67)
PS: Logit	1.39** (0.62)	1.69** (0.81)	1.32** (0.62)	3.74** (1.72)
Covariates: Value chain	1.43** (0.72)	1.99* (1.03)	1.13 (0.68)	1.84** (0.73)
Covariates: ln(No. funded agri-start-ups)	1.17* (0.67)	2.02** (0.93)	1.23* (0.65)	4.12** (1.86)

Note: Coefficients for the independent variable accelerator participation for alternative specifications. Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

We find that estimating the IPTW approach using a trimmed sample results in estimated coefficients and standard errors that are comparable to the baseline except for large investments. This observation suggests that the estimated treatment effect on the likelihood of raising investment is not unduly influenced by the leverage points at the tails of the distribution. Similarly, when employing alternative weighting methods, that is logit instead of CBPS, the estimates for coefficients and standard errors remain consistent with the baseline values. These findings further strengthen the internal validity of our results and suggest that the estimated treatment effects demonstrate robustness to the specific choice of weighting method. Furthermore, when including indicators of the value chain coverage (e.g., logistics) of the start-up we observe robustness of our main findings for the investment outcomes. Finally, all baseline results demonstrate robustness to variations in the measurement of ecosystem maturity.

In the subsequent analysis we investigate potential violations of the unconfoundedness assumption which underlies our identification strategy. In a pseudo outcome estimation, we find that participating in the accelerator has no effect on pre-treatment investment, even when excluding pre-treatment investment from the weighting. This can be interpreted as evidence supportive of the assumption of unconfoundedness as the true effect is a priori known to be zero (Imbens, 2015). Further, the E-value sensitivity analysis suggests that only an unmeasured confounder that makes otherwise similar start-ups about 50% more likely to be selected into the accelerator and about 50% more likely to experience the outcome (net of all observed covariates) would shift the 90% confidence interval to include the null. None of our observed start-ups characteristics shows associations of this magnitude with selection and outcome, and prior work suggests that start-up characteristics rarely exhibit such strong explanatory power for venture outcomes (McKenzie & Sansone, 2019). We therefore view the sensitivity results as strengthening confidence in our main findings. However, because unobserved confounding of the indicated level cannot be ruled out entirely, they cannot be taken as definitive proof of identification. Details are presented in the supplementary materials.

Given that our sample size provides moderate statistical power below the conventional threshold of 80%, we further assessed the robustness of our results using Gelman and Carlin (2014)'s diagnostic framework; despite already finding consistent evidence that accelerator participation significantly enhances venture investment. Gelman and Carlin (2014)'s approach indicates that the probability of the true effect having the opposite (negative) direction is virtually zero, though the reported effect sizes might be somewhat inflated, on average by up to 25%. Even after accounting for this potential exaggeration, the positive impact of accelerator participation remains economically meaningful, underscoring the robustness of the positive impact that accelerators can provide for entrepreneurial ventures. Details of the power analysis are provided in the supplementary materials.

4.3 Results for Hypothesis 2: Ecosystem contingency of accelerator effectiveness

Hypothesis 2a tests the substitution view, predicting that accelerators will have greater effect on start-ups' realized growth finance the lower the maturity of the EE. By contrast, Hypothesis 2b tests the complementarity view, predicting that accelerators will have greater impact the higher the maturity of the EE. To test both hypotheses, we include an interaction term between accelerator participation and the maturity of the entrepreneurial ecosystem to analyze the direction this interaction. The results are presented in Table 5.

We find that start-ups located in more mature ecosystems derive greater benefits from accelerator participation in their likelihood of raising investment in line with the prediction of the complementarity view and opposing the prediction of the substitution view. The effect is statistically significant at the 5% level. Further, while we find a similar positive moderating effect of ecosystem maturity on investment larger than USD 100,000 and remaining operational, these are not statistically significant at the 10% level. By contrast, the estimation indicates that an accelerator's ability to help start-ups raise grant financing is higher in less mature ecosystems, but is statistically insignificant.

Table 5: Moderating effect of ecosystem maturity on the estimated impact of accelerator participation on start-up investment (H2 baseline)

	Main DV	*Alternative DVs for robustness*		
	Investment	Investment>$100k	Grant	Operational
	(1)	(2)	(3)	(4)
Participation × ln(No. funded start-ups)	1.03^{**}	0.49	−0.16	0.90
	(0.47)	(0.45)	(0.52)	(0.69)
Accelerator participation	−3.30	−0.78	1.99	0.33
	(2.27)	(2.25)	(2.57)	(3.68)
ln(No. funded start-ups)	−0.09	−0.28	−0.29	0.22
	(0.35)	(0.34)	(0.50)	(0.35)
Intercept	−1.23	−8.96	−3.98	-4.75^{**}
	(3.45)	(6.00)	(3.36)	(2.27)
Controls	Yes	Yes	Yes	Yes
Country & cohort dummies	Yes	Yes	Yes	Yes
Observations	133	133	133	133

Note: ln(No. of funded start-ups) is the (logged) ecosystem maturity measure (log of the number of funded start-ups in the last decade in a start-up's country). Participation × ln(No. of funded start-ups) is the interaction term between the binary treatment indicator (accelerator participation) and the logged ecosystem maturity measure. Coefficients for estimation of H2. Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

To aid interpretation of the interaction model, Figure 2 translates the estimated logit coefficients into changes in predicted probabilities of raising investment. For each value of ecosystem maturity (shown from the 20th to the 80th percentile), we compute the predicted probability of investment for otherwise identical start-ups under two scenarios—participating in the accelerator versus not participating—and plot the difference in percentage points. The figure shows that the implied effect of accelerator participation is increasing in ecosystem maturity: at low maturity levels the estimated probability change is small and close to zero, while at higher maturity levels participation is associated with a noticeably larger increase in the likelihood of investment, e.g., at the 80th percentile of ecosystem maturity participating in the accelerator leads to a 50% increase in the likelihood of raising investment. Because these effects are computed holding covariates at a reference profile, the magnitudes should be interpreted as illustrative model-implied effects for a representative case, rather than as universal effects for all start-ups.

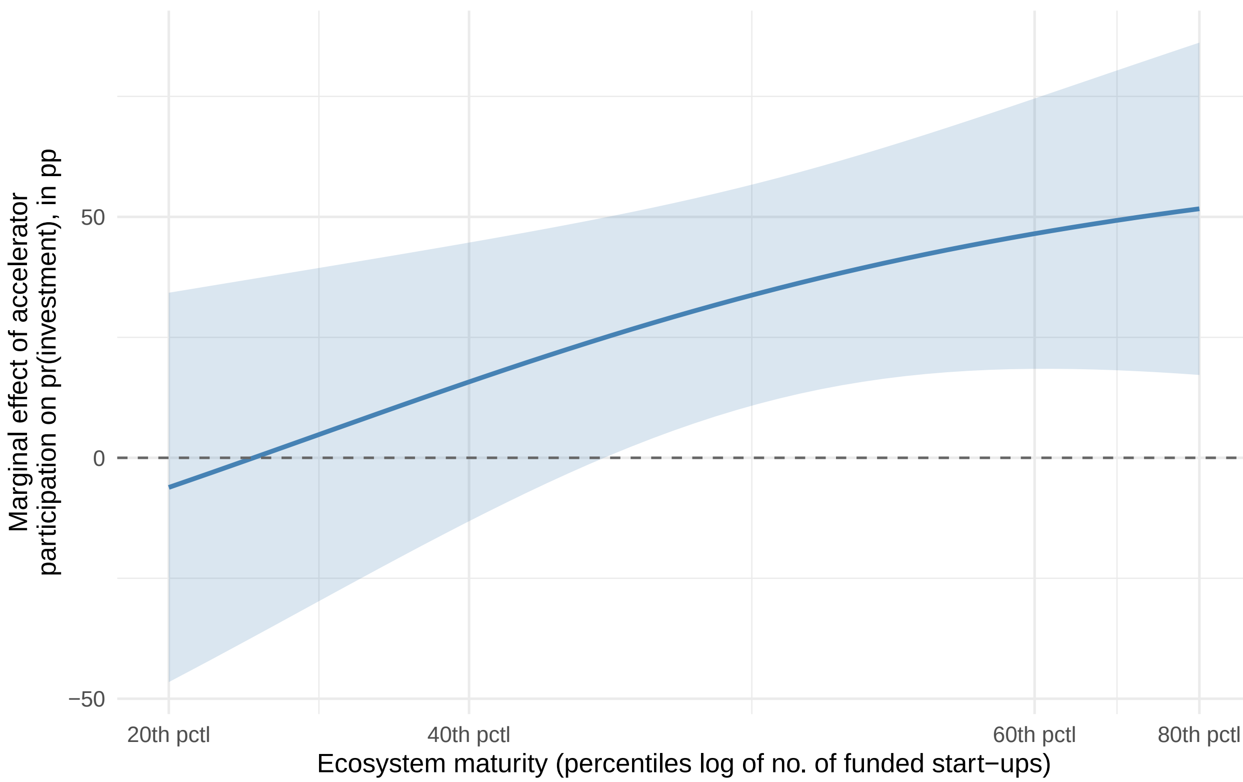

Figure 2: Marginal effect of accelerator participation on the probability of investment across ecosystem maturity (reference covariate profile; shaded area shows 90% confidence interval)

In further analysis reported in the supplementary materials, we find that a start-up's ecosystem maturity also moderates an accelerator's effectiveness with respect to the amount of investment a start-up receives: Start-ups in more mature ecosystems accrue higher benefits from acceleration in terms of the amount of investment raised after the program. This effect is statistically significant at the 5% level.

4.4 Robustness of results for Hypothesis 2

These findings exhibit robustness for most alternative estimation strategies. In alignment with the robustness checks conducted for Hypothesis 1, we apply our baseline specification to various adjustments, including sample trimming, alternative weighting methods, variations in covariate selection, and different operationalizations of ecosystem maturity. Table 6 presents the coefficient of the interaction term between accelerator participation and the number of funded start-ups within the respective national ecosystem across the mentioned alterations.

Table 6: Robustness of estimated effects of the interaction of ecosystem maturity and accelerator participation on start-up performance (H2)

	Main DV	*Alternative DVs for robustness*		
Specification	Investment (1)	Investment>\$100k (2)	Grant (3)	Operational (4)
Baseline	1.03** (0.47)	0.49 (0.45)	−0.16 (0.52)	0.90 (0.69)
Trimmed sample	1.13** (0.48)	0.64 (0.45)	−0.11 (0.48)	1.05 (0.90)
PS: Logit	1.05** (0.47)	0.54 (0.44)	−0.27 (0.52)	0.81 (0.65)
Covariates: ln(No. funded agri-start-ups)	0.80 (0.59)	0.55 (0.57)	−0.08 (0.64)	0.38 (0.44)

Note: Coefficients for the interaction of accelerator participation with the ecosystem maturity variable for alternative specifications. Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Consistent with the baseline results for our main model for investment, reestimating with a trimmed sample and using a different estimation of the propensity score suggest that the accelerator exerts a more pronounced positive effect on the capacity of a start-up to raise investment in more mature entrepreneurial ecosystems. But for our more narrow indicator of the maturity of start-up's ecosystem, being the count of funded start-ups in the agriculture sector within a national ecosystem, we do not observe a significant moderating effect.

For alternative outcomes, in line with the baseline, the alternative specifications do not provide evidence that ecosystem maturity moderates an accelerator's impact on other outcomes, including start-ups' ability to raise grants and remain operational.

For H2, the E-value sensitivity analysis again suggests that only an unmeasured confounder that makes otherwise similar start-ups about 50% more likely to be selected into the accelerator and about 50% more likely to experience the outcome (net of all observed covariates) would shift the 90% confidence interval to include the null. Details are provided in the supplementary materials.

Given the moderate statistical power available when testing Hypothesis 2, the insignificant results from models (2), (3) and (4) and for alternative covariates in model (1) should be interpreted with caution. Power analysis indicates that the minimum detectable effect is larger in magnitude than the observed coefficients. This suggests that the lack of statistical significance could reflect limited power, though it may also indicate that any true effects are modest or absent. By contrast, our main model (1) focusing on investments yields statistically significant estimates. Gelman and Carlin (2014)'s diagnostics indicate a very low probability (less than 1%) of a sign error and an expected exaggeration factor of approximately 1.65 implying that the reported coefficients may overstate the true effect by about 65%. Even under this conservative adjustment, the results highlight the importance of a supportive ecosystem in amplifying accelerator effectiveness. Details of the power analysis are provided in the supplementary materials.

5 Discussion

This study asks when and why start-up accelerators in emerging markets help ventures raise investment for scaling. Using data from a pan-African accelerator and a high-quality counterfactual group of narrowly rejected applicants, we find that accelerator participation is associated with a higher likelihood of raising investment and a higher volume of investment. Crucially, this association is ecosystem-contingent: effects are significantly stronger in more mature entrepreneurial ecosystems. This pattern is more consistent with a complementarity view of accelerators as ecosystem intermediaries rather than with a pure substitution view.

5.1 Contributions to research on supporting ventures and entrepreneurial ecosystems in emerging markets

Our first contribution is to provide empirical evidence of the positive effect of accelerator support for ventures in emerging markets. In a pan-African setting, we show economically meaningful gains in ventures' likelihood of raising investment after acceleration. This adds credible evidence from African contexts where accelerators have proliferated rapidly, yet evaluation evidence remains scarce (Assenova & Agarwal, 2025; Lay & Tafese, 2025). This empirical evidence challenges recent quantitative studies in emerging market contexts where effects have been found to be more ambiguous (Cusolito et al., 2021; Gonzalez-Uribe & Leatherbee, 2018), and have called into question the use of accelerator templates from high-income countries (Haines, 2014; Lall et al., 2020). Our results suggest a possible answer to this puzzle. We show that accelerators have a positive effect in supporting ventures when they can amplify other complementary aspects of the ecosystem.

This leads us to our second contribution which advances a complementarity view of acceleration in emerging markets. This view challenges the predominant view that emphasizes gap-filling with support organizations substituting for missing markets, institutions and further resources (Bade, 2026; Dutt et al., 2015; McKenzie & Woodruff, 2014). In contrast, our results are consistent with accelerators operating as amplifiers: their mentoring, capability-building, peer learning, and network building are more effective where complementary ecosystem resources, institutions and actors are already present. Building on evidence from the United States that accelerator impacts are larger where specific key complements, that is proximate investors and dense start-up event infrastructure, are available (Fehder, 2024), we generalize this insight to the contexts of emerging markets and show that heterogeneous accelerator outcomes track ecosystem maturity as a system-level condition. Here, we contribute by shifting from contingency on individual ecosystem elements to the contingency on the joint and complex configuration of all ecosystem elements (Stam & van de Ven, 2021). These insights resonate with recent calls to move beyond a gap-filling, Western-centric assessment of the institutional foundations of entrepreneurship in informal and emerging economies (Nason & Bothello, 2023) and towards acknowledging the diversity of contexts especially on the African continent (Farhoud et al., 2023). Future research could unpack how complementarities between accelerators and other resources and institutions operate across different emerging market contexts.

Our third contribution is to provide an output-based proxy for ecosystem maturity: historical counts of funded start-ups. Methodologically, this allows us to speak to EE measurement debates. Our proxy is an indirect way of capturing ecosystem capacity to generate investable ventures and is theoretically aligned with our outcome of interest, investment. It is also practical in data-scarce settings where component-level measures are incomplete (Hess et al., 2025; Johnson et al., 2022; Leendertse et al., 2022; Stam et al., 2025). However, precisely because it is an aggregate output proxy, it is best suited for identifying a boundary condition rather than isolating which specific ecosystem elements drive the complementarity (Bade, 2026). Future research will require alternative methodological approaches to understand these complementarities. Large-scale, quantitative analyses are likely to be limited in providing answers as to how these complementarities operate. Instead, we call for bottom-up, theory-building approaches that develop clear explanations of why and how certain patterns of ecosystem components work in specific contexts. This would support calls for moving beyond measuring ecosystem outcomes and instead focusing on underlying ecosystem processes (Spigel & Harrison, 2018; Stam, 2015).

5.2 Managerial and policy implications

For founders, our results underscore that entrepreneurial ecosystems are not merely background conditions but shape start-ups' ability to secure growth finance. Investment-oriented support is more likely to be effective when ventures are embedded in mature ecosystems, e.g., with dense investor, mentor, and peer networks. Accordingly, when selecting an accelerator, founders should evaluate not only program features but also the accelerator's ecosystem position including its ability to mobilize high-quality local mentors, broker access to investors active in that ecosystem, provide credible visibility within that specific hub and have peers and alumni for networking from their ecosystem. Further, where home ecosystems are less mature, our results imply that founders may need to bundle accelerator participation with deliberate ecosystem-spanning strategies that replicate the complements accelerators leverage in mature hubs. Rather than treating an accelerator as a purely local intervention, ventures can use it as a bridge to distant ecosystems by reorienting network targets (Rawhouser et al., 2024), accelerating internationalization (Adomako et al., 2019), or relocating fundraising activities through holding companies abroad while keeping core operations in the home market (Robinson, 2025).

For accelerator managers and sponsors, our results provide quantitative evidence that acceleration can improve ventures' access to growth finance in emerging markets, underscoring the value of investment-oriented designs such as structured investment-readiness work. At the same time, ecosystem characteristics should be treated as a core design parameter. Consistent with evidence that accelerator impacts are larger when key complements (e.g., investors and entrepreneurial community activity) are nearby, sponsors can maximize expected impact by concentrating operations in mature hubs (Fehder, 2024). When the strategic objective is instead to support ventures in less mature ecosystems, common in emerging-market policy and development practice, standard cohort programming is unlikely to be sufficient. Mitigating this boundary condition requires tailoring and local embedding: For instance, building strong local mentor networks and partnerships, drawing in external investors through cross-border pipelines, providing hands-on transaction support (e.g., diligence and term-sheet readiness), and sustaining engagement long enough for networks and deal processes to develop.

For policymakers, the findings caution against viewing accelerators as stand-alone solutions to helping start-ups scale and attract investment. If accelerators are more effective in more mature ecosystems, then intended outcomes are more likely when acceleration is combined with policy mixes that strengthen the broader entrepreneurial ecosystem. This shifts policy attention from funding accelerators per se toward designing appropriate bundles and sequences of ecosystem-building and venture-building instruments that relax the binding constraints in a given place (Wang et al., 2022).

5.3 Limitations and future research

Several limitations qualify inference and point to future work. First, we study a single accelerator. This affords measurement depth but limits claims about generalizability across accelerator types (e.g., donor-backed versus equity-driven) and sector focus. While robustness results indicate that the moderating effect of ecosystem maturity on accelerator effectiveness is not driven by ecosystem elements exclusively relevant to agriculture start-ups, but by characteristics reflected in our industry-agnostic measure of ecosystem maturity, multi-accelerator and multi-country replications are needed to establish how broadly ecosystem-contingent effects travel.

Second, our design mitigates selection concerns using narrowly rejected applicants and

IPTW with rich covariates including application scores, unobserved differences may remain (Assenova & Amit, 2024; Hallen et al., 2020). Complementary designs, ideally randomized-control trials, would strengthen causal claims.

Third, our ecosystem maturity measure is intentionally aggregate. In EE terms, it captures an ecosystem's revealed capacity to generate investable ventures, but it does not "unbox" which underlying EE elements and interdependencies drive that capacity (Stam & van de Ven, 2021; Stam et al., 2025). Future research should therefore link output-based maturity proxies to specific ecosystem complements in emerging markets by measuring, for example, the depth and composition of local and cross-border investors, the presence of specialized intermediaries (legal, accounting, due diligence support), and the frictions of contracting and deal execution.

Fourth, results for some secondary outcomes are less conclusive but potentially informative. For grant funding, we observe fewer events in our sample, which implies less variation in the outcome and therefore substantially lower statistical power to detect moderation by ecosystem maturity. Substantively, grant allocation may also be shaped by donor preferences and nonlocal networks, which could attenuate or even reverse ecosystem contingency relative to market-based investment. Taken together, while we avoid strong inference given limited power, the pattern is consistent with ecosystem complementarity being most salient for "mainstream" investment transactions that depend on investor matching and deal execution capacity within (or brokered through) the ecosystem.

Finally, we focus on venture outcomes rather than downstream development impacts which is in particular salient in many ecosystems in emerging markets. Future studies could explore whether ecosystem-contingent start-up acceleration translates into sustained development outcomes in sectors central to emerging markets, e.g., jobs, incomes, climate resilience (Leendertse & Rijnsoever, 2025).

6 Conclusion

Taken together, our findings position accelerators in emerging markets as context-dependent ecosystem intermediaries: they can increase ventures' likelihood of raising investment, but the extent to which acceleration translates into realized investment depends on the maturity of the surrounding entrepreneurial ecosystem. This helps reconcile prior mixed evidence from emerging markets and suggests that transferring accelerator models across heterogeneous emerging markets without parallel attention to ecosystem complements is unlikely to yield uniform results.

References

Ács, Z. J., Autio, E., & Szerb, L. (2014). National systems of entrepreneurship: Measurement issues and policy implications. *Research Policy*, *43*, 476–494.

Adomako, S., Amankwah-Amoah, J., Dankwah, G. O., Danso, A., & Donbesuur, F. (2019). Institutional voids, international learning effort and internationalization of emerging market new ventures. *Journal of International Management*, *25*, 100666.

Aldrich, H. E., & Kim, P. H. (2007). Small worlds, infinite possibilities? How social networks affect entrepreneurial team formation and search. *Strategic Entrepreneurship Journal*, *1*, 147–165.

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.

Armanios, D. E., Eesley, C. E., Li, J., & Eisenhardt, K. M. (2017). How entrepreneurs leverage institutional intermediaries in emerging economies to acquire public resources. *Strategic Management Journal*, *38*, 1373–1390.

Assenova, V. A. (2020). Early-stage venture incubation and mentoring promote learning, scaling, and profitability among disadvantaged entrepreneurs. *Organization Science*, *31*, 1560–1678.

Assenova, V. A. (2021). Institutional change and early-stage start-up selection: Evidence from applicants to venture accelerators. *Organization Science*, *32*, 407–432.

Assenova, V. A., & Agarwal, A. (2025). Entrepreneurship and innovation in Africa. In O. Sorenson & P. H. Thornton (Eds.), *De Gruyter Handbook of Sociology of Innovation and Entrepreneurship* (pp. 289–310).

Assenova, V. A., & Amit, R. (2024). Poised for growth: Exploring the relationship between accelerator program design and startup performance. *Strategic Management Journal*, *45*, 1029–1060.

Audretsch, D. B., Keilbach, M. C., & Lehmann, E. E. (2006). *Entrepreneurship and economic growth*. Oxford University Press.

Austin, P. C., & Stuart, E. A. (2015). Moving towards best practice when using inverse probability of treatment weighting (IPTW) using the propensity score to estimate causal treatment effects in observational studies. *Statistics in Medicine*, *34*, 3661–3679.

Avnimelech, G., Dushnitsky, G., Ellsaesser, F., & Fitza, M. (2025). Are accelerators akin to breweries or wineries? A Bayesian variance decomposition of accelerator and cohort effects. *Strategic Management Journal*, *46*, 534–579.

Bade, M. (2026). Ecosystem conditions and the efficacy of entrepreneurial support organizations: Moderating effects on venture entry. *Strategic Entrepreneurship Journal*, *in press*.

Bafera, J., & Kleinert, S. (2023). Signaling theory in entrepreneurship research: A systematic review and research agenda. *Entrepreneurship: Theory and Practice*, *47*, 2419–2464.

Barrett, C. B., Christian, P., & Shiferaw, B. A. (2017). The structural transformation of African agriculture and rural spaces. *Agricultural Economics*, *48*, 5–10.

Baum, J. A. C., & Oliver, C. (1991). Institutional linkages and organizational mortality. *Administrative Science Quarterly*, *36*, 187–218.

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.

Bischoff, K. M., Gielnik, M. M., & Frese, M. (2020). When capital does not matter: How entrepreneurship training buffers the negative effect of capital constraints on business creation. *Strategic Entrepreneurship Journal*, *14*, 369–395.

Brown, T. (2022). Skill ecosystems in the Global South: Informality, inequality, and community setting. *Geoforum*, *132*, 10–19.

Busch, C., & Barkema, H. (2022). Planned luck: How incubators can facilitate serendipity for nascent entrepreneurs through fostering network embeddedness. *Entrepreneurship: Theory and Practice*, *46*, 884–919.

Bustamante, C. V., Mingo, S., & Matusik, S. F. (2021). Institutions and venture capital market creation: The case of an emerging market. *Journal of Business Research*, *127*, 1–12.

Cai, J., & Szeidl, A. (2018). Interfirm relationships and business performance. *The Quarterly Journal of Economics*, *133*, 1229–1282.

Cao, Z., & Shi, X. (2021). A systematic literature review of entrepreneurial ecosystems in advanced and emerging economies. *Small Business Economics*, *57*, 75–110.

Casanova, L., Cornelius, P., & Dutta, S. (2018). *Financing entrepreneurship and innovation in emerging markets*. Academic Press.

Chang, M. H., & Assenova, V. A. (2026). Founders' pre-entry knowledge and the heterogeneous returns to accelerator participation. *Strategic Management Journal*, *47*, 726–757.

Clingingsmith, D., & Shane, S. (2018). Training aspiring entrepreneurs to pitch experienced investors: Evidence from a field experiment in the United States. *Management Science*, *64*, 5164–5179.

Cohen, S., Fehder, D. C., Hochberg, Y. V., & Murray, F. (2019). The design of startup accelerators. *Research Policy*, *48*, 1781–1797.

Cusolito, A. P., Dautovic, E., & McKenzie, D. (2021). Can government intervention make firms more investment ready? A randomized experiment in the Western Balkans. *The Review of Economics and Statistics*, *103*, 428–442.

Dealroom. (2024). Accelerator and start-up database.

Dushnitsky, G., & Sarkar, S. (2022). Here comes the sun: The impact of incidental contextual factors on entrepreneurial resource acquisition. *Academy of Management Journal*, *65*, 66–92.

Dutt, N., Hawn, O., Vidal, E., Chatterji, A., McGahan, A., & Mitchell, W. (2015). How open system intermediaries address institutional failures: The case of business incubators in emerging-market countries. *Academy of Management Journal*, *59*, 818–840.

Eddleston, K. A., Ladge, J. J., Mitteness, C., & Balachandra, L. (2016). Do you see what I see? Signaling effects of gender and firm characteristics on financing entrepreneurial ventures. *Entrepreneurship: Theory and Practice*, *40*, 489–514.

Eslava, M., Haltiwanger, J., & Pinzón, Á. (2022). Job creation in Colombia versus the USA: 'up-or-out dynamics' meet 'the life cycle of plants'. *Economica*, *89*, 511–539.

Farhoud, M., Bignotti, A., Hamann, R., Kauami, N. C., Kiconco, M., Ghalwash, S., Beule, F. D., Tladi, B., Matomela, S., & Kgaphola, M. (2023). African perspectives on researching social entrepreneurship. *Social Enterprise Journal*, *19*, 421–434.

Fehder, D. C. (2024). Coming from a good pond: The influence of a new venture's founding ecosystem on accelerator performance. *Administrative Science Quarterly*, *69*, 1–38.

Field, L., Cruz, M., Pereira-Lopex, M., & David, H. (2025). *Venture capital and the rise of africa's tech startups*. International Finance Corporation, World Bank.

Flynn, D. (1993). Sponsorship and the survival of new organizations. *Journal of Small Business Management*.

Gelman, A., & Carlin, J. (2014). Beyond power calculations: Assessing Type S (sign) and Type M (magnitude) errors. *Perspectives on Psychological Science*, *9*, 641–651.

Giudici, A., Reinmoeller, P., & Ravasi, D. (2018). Open-system orchestration as a relational source of sensing capabilities: Evidence from a venture association. *Academy of Management Journal*, *61*, 1369–1402.

Gonzalez-Uribe, J., & Leatherbee, M. (2018). The effects of business accelerators on venture performance: Evidence from Start-Up Chile. *The Review of Financial Studies*, *31*, 1566–1603.

González-Uribe, J., & Reyes, S. (2021). Identifying and boosting "gazelles": Evidence from business accelerators. *Journal of Financial Economics*, *139*, 260–287.

Goswami, K., Mitchell, R. J., & Bhagavatula, S. (2018). Accelerator expertise: Understanding the intermediary role of accelerators in the development of the Bangalore entrepreneurial ecosystem. *Strategic Entrepreneurship Journal*, *12*, 117–150.

Greenwood, R., Raynard, M., Kodeih, F., Micelotta, E. R., & Lounsbury, M. (2011). Institutional complexity and organizational responses. *Academy of Management Annals*, *5*, 317–371.

Guerrero, M. (2021, March). The role of incubators and accelerators in the Latin American entrepreneurship and innovation ecosystems. In S. A. Mian, M. Klofsten, & W. Lamine (Eds.), *Handbook of Research on Business and Technology Incubation and Acceleration* (pp. 335–350). Edward Elgar Publishing.

Haines, J. K. (2014). Iterating an innovation model: Challenges and opportunities in adapting accelerator practices in evolving ecosystems. *Ethnographic Praxis in Industry Conference Proceedings*, *2014*, 282–295.

Hallen, B. L. (2008). The causes and consequences of the initial network positions of new organizations: From whom do entrepreneurs receive investments? *Administrative Science Quarterly*, *53*, 685–718.

Hallen, B. L., Cohen, S., & Bingham, C. B. (2020). Do accelerators work? If so, how? *Organization Science*, *31*, 245–534.

Hallen, B. L., Cohen, S., & Park, S. H. (2023). Are seed accelerators status springboards for startups? Or sand traps? *Strategic Management Journal*, *44*, 2060–2096.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? Small versus large versus young. *The Review of Economics and Statistics*, *95*, 347–361.

Hess, S., Wahl, A., & Johnson, A. R. (2025). Measuring entrepreneurial ecosystems across levels: A district approach. *Small Business Economics*, *65*, 1617–1649.

Hirano, K., Imbens, G. W., & Ridder, G. (2003). Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica*, *71*, 1161–1189.

Imai, K., & Ratkovic, M. (2014). Covariate balancing propensity score. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *76*, 243–263.

Imbens, G. W. (2015). Matching methods in practice: Three examples. *Journal of Human Resources*, *50*, 373–419.

Johnson, E., Hemmatian, I., Lanahan, L., & Joshi, A. M. (2022). A framework and databases for measuring entrepreneurial ecosystems. *Research Policy*, *51*, 104398.

Khayesi, J. N., & George, G. (2011). When does the socio-cultural context matter? Communal orientation and entrepreneurs' resource accumulation efforts in Africa. *Journal of Occupational and Organizational Psychology*, *84*, 471–492.

Khayesi, J. N., George, G., & Antonakis, J. (2014). Kinship in entrepreneur networks: Performance effects of resource assembly in Africa. *Entrepreneurship: Theory and Practice*, *38*, 1323–1342.

Krishnan, R., Cook, K. S., Kozhikode, R. K., & Schilke, O. (2021). An interaction ritual theory of social resource exchange: Evidence from a Silicon Valley accelerator. *Administrative Science Quarterly*, *66*, 659–710.

Lall, S. A., Chen, L. W., & Roberts, P. W. (2020). Are we accelerating equity investment into impact-oriented ventures? *World Development*, *131*, 104952.

Lawrence, T. B., & Suddaby, R. (2006). Institutions and institutional work. In S. R. Clegg, C. Hardy, T. B. Lawrence, & W. R. Nord (Eds.), *Handbook of Organization Studies* (2nd ed., pp. 215–254). Sage.

Lay, J., & Tafese, T. (2025). Africa's emergent tech sector: Characteristics and development implications. *Africa Spectrum*, *60*, 106–126.

Leendertse, J., & Rijnsoever, F. V. (2025). Greening pastures: Ecosystems for sustainable entrepreneurship. *Small Business Economics*, *65*, 1595–1616.

Leendertse, J., Schrijvers, M., & Stam, E. (2022). Measure twice, cut once: Entrepreneurial ecosystem metrics. *Research Policy*, *51*, 104336.

Marquis, C., & Raynard, M. (2015). Institutional strategies in emerging markets. *Academy of Management Annals*, *9*, 291–335.

McKenzie, D., & Sansone, D. (2019). Predicting entrepreneurial success is hard: Evidence from a business plan competition in Nigeria. *Journal of Development Economics*, *141*, 102369.

McKenzie, D., & Woodruff, C. (2014). What are we learning from business training and entrepreneurship evaluations around the developing world? *The World Bank Research Observer*, *29*, 48–82.

Monitor, G. E. (2025). *Global Entrepreneurship Monitor 2024/2025 global report: Entrepreneurship reality check* (S. Hill, A. Ionescu-Somers, & A. Coduras, Eds.). Global Entrepreneurship Research Association (GERA).

Mulugetta, Y., Sokona, Y., Trotter, P. A., Fankhauser, S., Omukuti, J., Croxatto, L. S., Steffen, B., Tesfamichael, M., Abraham, E., Adam, J. P., Agbemabiese, L., Agutu, C., Aklilu, M. P., Alao, O., Batidzirai, B., Bekele, G., Dagnachew, A. G., Davidson, O., Denton, F., … Yussuff, A. (2022). Africa needs context-relevant evidence to shape its clean energy future. *Nature Energy*, *7*, 1015–1022.

Nason, R., & Bothello, J. (2023). Far from void: How institutions shape growth in informal economies. *Academy of Management Review*, *48*, 485–503.

Plummer, L. A., Allison, T. H., & Connelly, B. L. (2015). Better together? Signaling interactions in new venture pursuit of initial external capital. *Academy of Management Journal*, *59*, 1585–1604.

Qin, F. (2025). Oasis in the desert or icing on the cake? The impact of entrepreneurship accelerators across ecosystems. *Journal of International Business Studies*, *56*, 659–676.

Rawhouser, H., Sutter, C., Holzaepfel, N., Conger, M., & Newbert, S. L. (2024). Knowledge-related resourcefulness for growth in weak entrepreneurial ecosystems. *Entrepreneurship: Theory and Practice*, *49*, 159–195.

Rechter, E., & Avnimelech, G. (2024). Intensive personal mentoring: Accelerators' secret sauce. *Small Business Economics*, *64*, 1259–1284.

Roberts, P. W., & Lall, S. A. (2019). Acceleration in emerging markets. In *Observing Acceleration* (pp. 135–160). Palgrave Macmillan, Cham.

Robinson, L. (2025). Mastering the flip: A guide for African startups seeking international investment.

Roche, M. P., Oettl, A., & Catalini, C. (2024). Proximate (co-)working: Knowledge spillovers and social interactions. *Management Science*, *70*, 8217–9119.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*, 41–55.

Spigel, B., & Harrison, R. (2018). Toward a process theory of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal*, *12*, 151–168.

Stam, E. (2015). Entrepreneurial ecosystems and regional policy: A sympathetic critique. *European Planning Studies*, *23*, 1759–1769.

Stam, E., Nkontwana, P., McDonald, R., Murenzi, R., Addo, K. A., Bayuo, B., Baah, B., Riezebos, S., & Gelissen, T. (2025). Measuring national entrepreneurial ecosystems in Africa. *Working Paper*.

Stam, E., & van de Ven, A. (2021). Entrepreneurial ecosystem elements. *Small Business Economics*, *56*, 809–832.

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, *25*, 1–21.

Sutter, C., Webb, J., Kistruck, G., Ketchen, D. J., & Ireland, R. D. (2017). Transitioning entrepreneurs from informal to formal markets. *Journal of Business Venturing*, *32*, 420–442.

Sydow, A., Cannatelli, B. L., Giudici, A., & Molteni, M. (2022). Entrepreneurial workaround practices in severe institutional voids: Evidence from Kenya. *Entrepreneurship: Theory and Practice*, *46*, 331–367.

Wang, H., Zhao, T., Cooper, S. Y., Wang, S., Harrison, R. T., & Yang, Z. (2022). Effective policy mixes in entrepreneurial ecosystems: A configurational analysis in China. *Small Business Economics*, *60*, 1509–1542.

Weele, T. J. V. D., & Ding, P. (2017). Sensitivity analysis in observational research: Introducing the E-Value. *Annals of Internal Medicine*, *167*, 268–274.

Woolley, J. L., & MacGregor, N. (2022). The influence of incubator and accelerator participation on nanotechnology venture success. *Entrepreneurship: Theory and Practice*, *46*, 1717–1755.

Zietsma, C., & Lawrence, T. B. (2010). Institutional work in the transformation of an organizational field: The interplay of boundary work and practice work. *Administrative Science Quarterly*, *55*, 189–221.

Zimmerman, M. A., & Zeitz, G. J. (2002). Beyond survival: Achieving new venture growth by building legitimacy. *Academy of Management Review*, *27*, 414–431.

Supplementary materials

Contents

S1 Selection process of the SAIS accelerator

The application to SAIS entails a rigorous three-stage selection process, as illustrated in Figure 3. Initially, start-ups are required to submit an online application that provides comprehensive information regarding the founding team, business model, and past performance. Applications are first screened for completeness and compliance with eligibility criteria, which specifically require that start-ups are for-profit entities in the agriculture and food sectors with established customer traction. Subsequently, eligible applicants are independently evaluated by three jury members across five dimensions: (i) quality of the founding team, (ii) clarity of the business model, (iii) innovativeness, (iv) product-market fit and scalability, and (v) demonstrated customer traction and financial health. The jury panel consists of SAIS staff members and external experts actively engaged in the African entrepreneurial ecosystem, including investors and start-up advisors. Finally, the highest-scoring applicants participate in structured interviews conducted by a minimum of three jury members, after which the final selection decisions are made by the SAIS committee. This final decision takes into consideration the quality of the application and the interview based on the scoring, variations in jury's scoring generosity, the potential incremental impact of the SAIS program, e.g., excluding start-ups that are already significantly funded, and the alignment of start-ups with the wider goals of the accelerator, e.g., improving climate resilience of farmers and increasing farmers' income. Each SAIS cohort accommodates 20 to 24 start-ups annually. Since 2022, SAIS has incorporated a segment specifically designed for French-speaking participants, allocating 5 to 7 places to enhance inclusivity among francophone applicants.

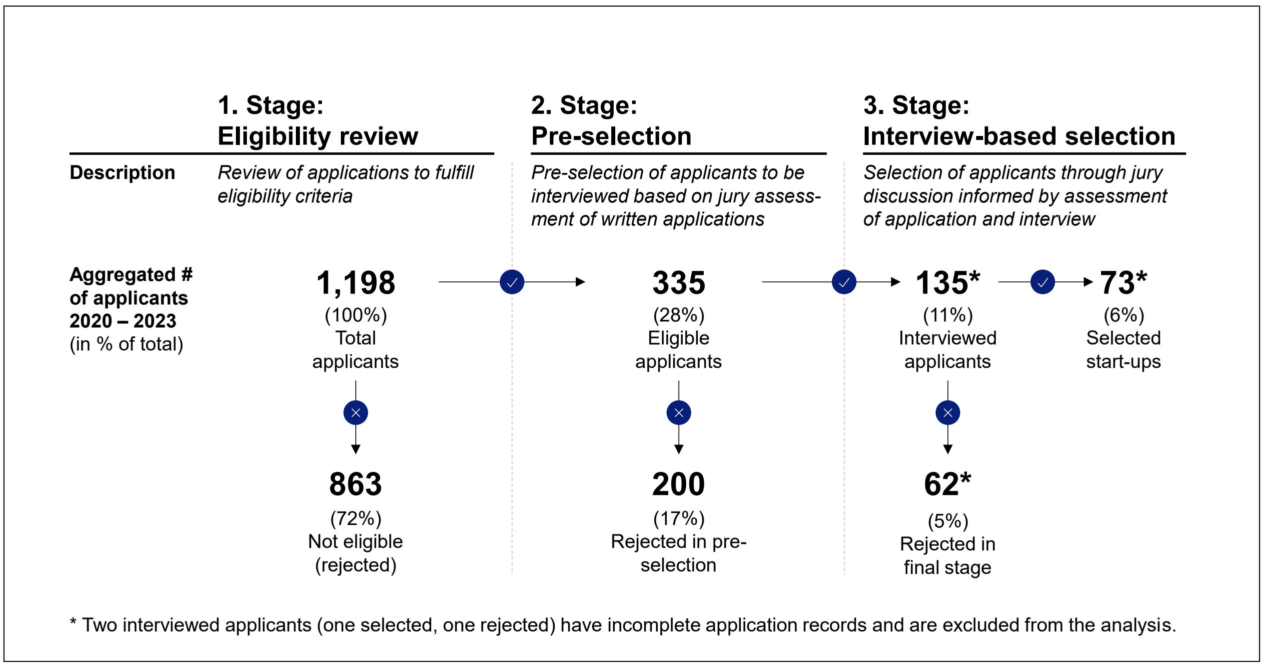

Figure 3: SAIS accelerator selection process and aggregated applicant numbers for cohorts 2020-2023

S2 Detailed sample description

Table 7 displays the summary statistics for our sample of interviewed start-ups split by selected and rejected start-ups. Further, Figure 4 depicts the start-up count by country of registration for start-ups in our sample.

Table 7: Sample description: Rejected and selected start-ups

		Rejected				Selected			
Section	Variable	Mean	Min	Max	SD	Mean	Min	Max	SD
Independent var	Accelerator participation	0.00	0.00	0.00	0.00	1.00	1.00	1.00	0.00
Dependent var	Raised investment post acceleration	0.11	0.00	1.00	0.32	0.28	0.00	1.00	0.45
	Raised investment >$100k post acceleration	0.05	0.00	1.00	0.22	0.18	0.00	1.00	0.39
	Raised grant post acceleration	0.08	0.00	1.00	0.28	0.18	0.00	1.00	0.39
	Operational post acceleration	0.85	0.00	1.00	0.36	0.93	0.00	1.00	0.26
Start-up var	Application score	0.42	0.00	0.75	0.17	0.59	0.22	0.82	0.11
	Revenue in $mn	0.21	0.00	5.00	0.66	0.32	0.00	4.00	0.73
	ln(Revenue in $)	10.25	0.00	15.42	2.67	10.76	0.00	15.20	2.85
	Company age	3.28	0.03	12.89	2.47	3.41	0.41	16.26	2.56
	Raised invest pre acceleration	0.18	0.00	1.00	0.39	0.26	0.00	1.00	0.44
	Raised grant pre acceleration	0.16	0.00	1.00	0.37	0.22	0.00	1.00	0.42
	Invest amount pre acceleration in $mn	0.05	0.00	2.20	0.28	0.23	0.00	4.70	0.75
	ln(Invest amount pre acceleration in $)	1.32	0.00	14.60	3.74	2.38	0.00	15.36	5.16
	Grant amount pre acceleration in $mn	0.00	0.00	0.07	0.01	0.03	0.00	1.35	0.17
	ln(Grant amount pre acceleration in $)	1.17	0.00	11.16	3.29	1.71	0.00	14.12	4.09
	Value chain: Inputs	0.08	0.00	1.00	0.28	0.08	0.00	1.00	0.28
	Value chain: Production	0.23	0.00	1.00	0.42	0.28	0.00	1.00	0.45
	Value chain: Post-Harvest	0.15	0.00	1.00	0.36	0.19	0.00	1.00	0.40
	Value chain: Logistics/Consumption	0.46	0.00	1.00	0.50	0.44	0.00	1.00	0.50
	Value chain: Finance	0.31	0.00	1.00	0.47	0.29	0.00	1.00	0.46
	Value chain: Planning	0.21	0.00	1.00	0.41	0.25	0.00	1.00	0.44
	Value chain: Farmer education	0.15	0.00	1.00	0.36	0.17	0.00	1.00	0.38
Ecosystem var	No. funded start-ups	159.74	0.00	453.00	168.00	183.42	0.00	453.00	171.98
	ln(No. funded start-ups)	4.04	0.00	6.12	1.78	4.43	0.00	6.12	1.52
	No. funded agri-start-ups	14.92	0.00	40.00	14.71	17.36	0.00	41.00	15.76
	ln(No. funded agri-start-ups)	2.01	0.00	3.71	1.45	2.26	0.00	3.74	1.33
Cohort var	Cohort French	0.26	0.00	1.00	0.44	0.14	0.00	1.00	0.35
	Cohort 2021	0.15	0.00	1.00	0.36	0.19	0.00	1.00	0.40
	Cohort 2022	0.31	0.00	1.00	0.47	0.33	0.00	1.00	0.47
	Cohort 2023	0.34	0.00	1.00	0.48	0.31	0.00	1.00	0.46

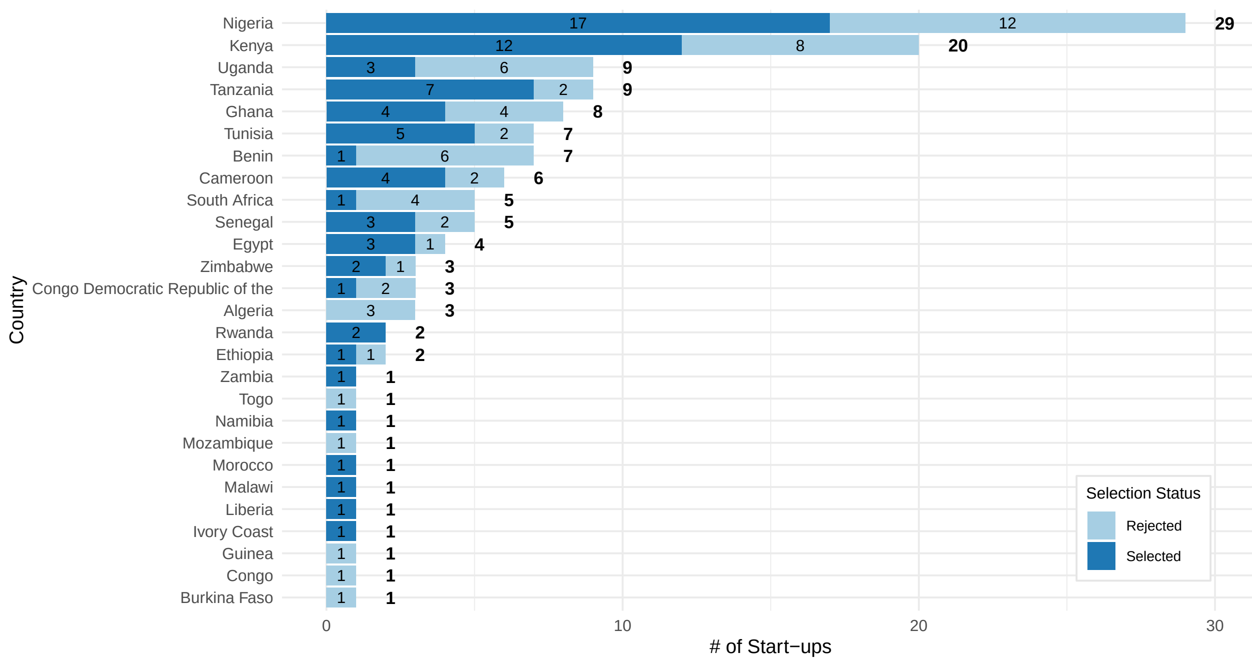

Figure 4: Number of interviewed start-ups by country of registration and selection status for cohorts 2020-2023

S3 IPTW sample diagnostics

Using the IPTW procedure described in the main part, we estimate the CBPS and use it to weight our sample of interviewed start-ups for which we use the R package weightIt (Greifer, 2025b). The quantitative and qualitative evaluation of covariate balance in the weighted sample is presented in Figures 5 and 6 generated using the R package cobalt (Greifer, 2025a).

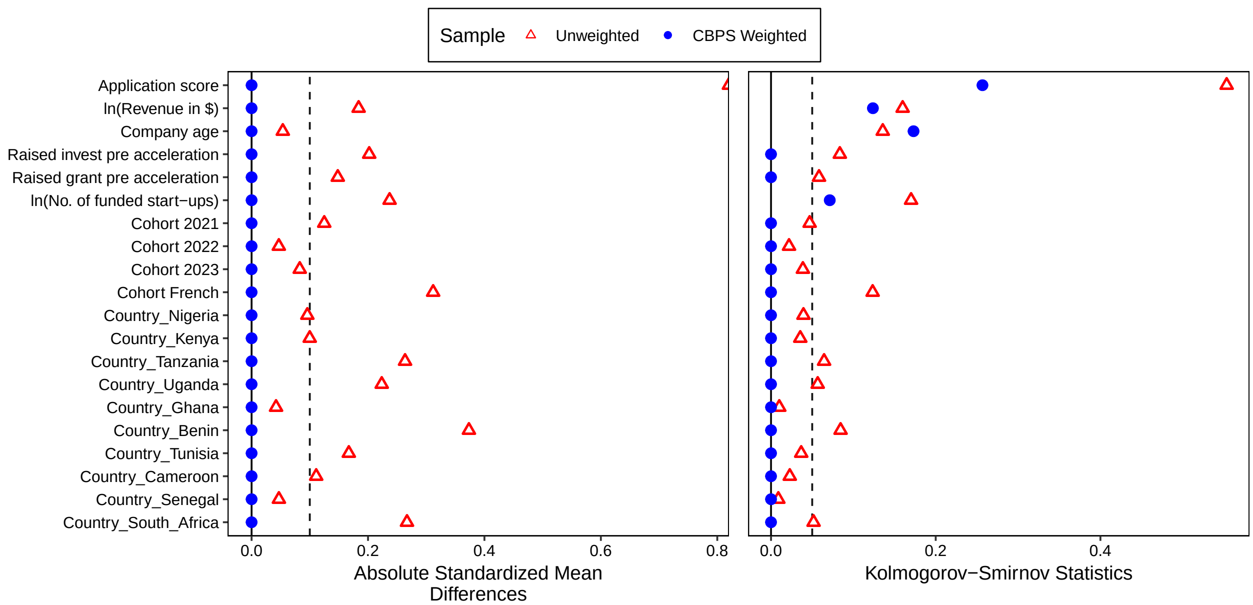

Figure 5: Distributional balance of covariates between treated and untreated start-ups, measured using standardized mean difference and the Kolmogorov-Smirnov statistic, for both the unweighted sample and the inverse-probability-of-treatment weighted (IPTW) sample (using covariate balancing propensity scores)

The comparison indicates that the IPTW approach results in balanced covariate distributions of selected and rejected start-ups in the weighted sample. Achieving a balanced weighted sample facilitates a consistent estimation of the treatment effect of accelerator participation on various outcomes, assuming the condition of unconfoundedness (Austin & Stuart, 2015).

In detail, the standardized mean difference between selected and rejected start-ups decreases for all covariates when compared to the unweighted sample (see Figure 5). A notable characteristic of the utilized CBPS is that the standardized means are nearly equivalent for selected and rejected start-ups in the weighted sample. Furthermore, the applica-

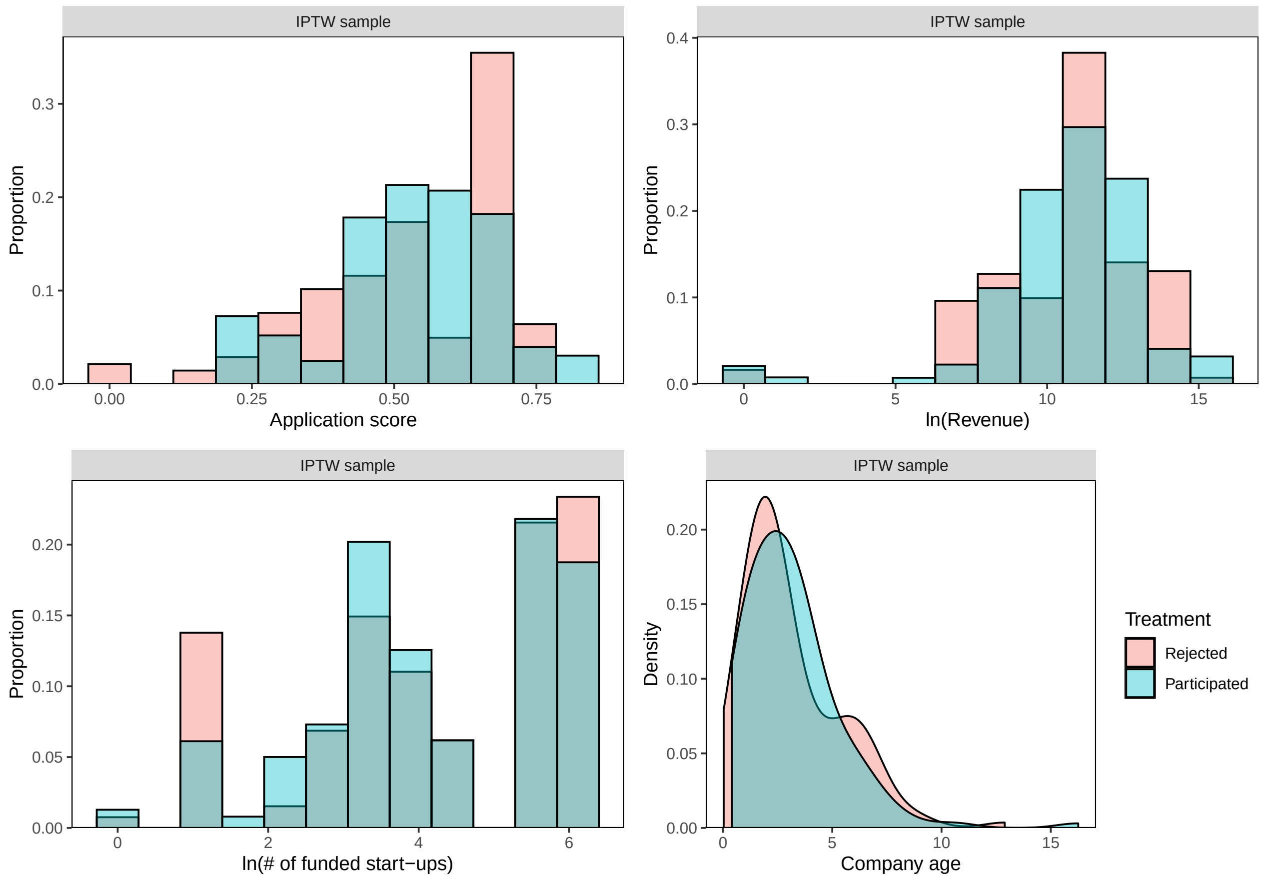

Figure 6: Distributional balance of selected covariates between treated and untreated start-ups for the inverse-probability-of-treatment weighted (IPTW) sample, analyzed graphically using sample distributions

tion of CBPS weighting leads to covariates exhibiting similarity in Kolmogorov-Smirnov statistics, which assess differences in distributions beyond the first moment by comparing the cumulative distribution functions of rejected and selected start-ups (Massey, 1951). We complement the quantitative analysis with a visual examination of the distributional densities of the CBPS weighted sample between the selected and rejected start-ups (see Figure 6). This analysis focuses on covariates that indicate some divergence in the Kolmogorov-Smirnov statistic (Ho et al., 2007), specifically the application score, ln(revenue), the ecosystem maturity indicator, and company age. The visual inspection suggests a notable similarity in the distributions of the selected and rejected start-ups for these covariates in the reweighted sample.

S4 Accelerator participation and the amount of investment raised

We complement the main analysis by examining whether accelerator participation affects not only the likelihood of raising external investment, but also the amount of investment raised following participation. We find that in line with the main result, participating in an accelerator increases the amount of investment raised in the emerging markets of our sample. Furthermore, start-ups located in more mature ecosystems benefit more from participating in the accelerator in terms of higher amounts of investment compared to start-ups in less mature ecosystems.

In detail, our empirical strategy mirrors the approach in the main text. We employ the same IPTW methodology using CBPS to estimate the average causal effect of accelerator participation on a start-up's amount of investment by reweighting observations based on their propensity scores. In contrast to the main section, where the dependent variable is a binary indicator of whether a start-up raises investment and we therefore estimate a weighted binomial model with a logit specification, here the outcome is continuous. Therefore, here, the dependent variable is the log of the amount of investment raised by start-up j within two years after the accelerator program. Accordingly, we estimate an IPTW-weighted linear model using ordinary least squares with robust standard errors to obtain the average treatment effect of accelerator participation on the post-application amount of investment raised.

Table 8 reports the results of this estimation. We find that participating in the accelerator increases the log of the amount of investment raised by 1.07, statistically significant at the 5% level. The coefficient can be interpreted as an increase of +192% in the amount of investment. Hence, participation in the accelerator nearly triples the amount of investment raised. This finding is robust across a range of alternative specifications and robustness checks (see Table 9). We do not find similar effects for an accelerator's impact on the log of amount of grant financing. This might be due to underlying structural reasons (e.g., grant amounts might be fixed in size, so accelerators only impact the likelihood), or due to our low power we are not able to identify an existing but more modest effect (see discussion of power in the main part and below in the supplementary material).

As in the main part we also investigate the moderating effect of the ecosystem maturity

Table 8: Estimated effects of accelerator participation on start-ups' investment amount

	Dependent variables	
	ln(Investment amount)	ln(Grant amount)
	(1)	(2)
Accelerator participation	1.07^{**}	0.41
	(0.50)	(0.47)
Application score	0.00	0.96
	(2.39)	(1.57)
ln(Revenue in $)	0.23	0.17^{*}
	(0.20)	(0.09)
Company age	−0.04	−0.08
	(0.14)	(0.10)
ln(Invest amount pre acceleration in $)	2.47^{***}	−0.52
	(0.94)	(0.65)
ln(Grant amount pre acceleration in $)	1.42^{*}	−0.53
	(0.83)	(0.74)
ln(No. funded start-ups)	−0.22	0.003
	(0.24)	(0.19)
Intercept	−2.29	−2.21
	(2.32)	(1.35)
Country & cohort dummies	Yes	Yes
Observations	133	133

Note: ln(No. funded start-ups) is the ecosystem maturity measure (log of the number of funded start-ups in the last decade in a start-up's country). Coefficients for estimation with OLS. Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 9: Estimated effect of accelerator participation on start-ups' investment amount for alternative specifications

Specification	ln(Investment amount)	ln(Grant amount)
Baseline	1.07** (0.50)	0.41 (0.47)
Trimmed sample	1.00** (0.47)	0.32 (0.48)
PS: Logit	1.20** (0.52)	0.48 (0.53)
Covariates: Value chain	1.25** (0.53)	0.33 (0.47)
Covariates: ln(No. funded agri-start-ups)	1.07** (0.49)	0.43 (0.47)

Note: OLS coefficients for accelerator participation. Standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

on an accelerator's ability to support start-ups in raising more investment. For this, we include an interaction term between accelerator participation and a start-up's ecosystem maturity in the above estimation in line with the main part. We find that start-ups in more mature ecosystems benefit more from acceleration in terms of higher amount of investment (see Table 10). This effect is statistically significant at the 5% level and largely robust to variations in the specification (see Table 11).

Table 10: Moderating effect of ecosystem maturity on the estimated impact of accelerator participation on start-ups' investment amount

	Dependent variables	
	ln(Investment amount)	ln(Grant amount)
	(1)	(2)
Participation × ln(No. funded start-ups)	0.85**	0.02
	(0.35)	(0.34)
Accelerator participation	−2.52	0.33
	(1.54)	(1.30)
ln(No. funded start-ups)	−0.49*	−0.003
	(0.28)	(0.25)
Intercept	−1.15	−2.19
	(2.24)	(1.61)
Controls	Yes	Yes
Country & cohort dummies	Yes	Yes
Observations	133	133

Note: ln(No. funded start-ups) is the (logged) ecosystem maturity measure (log of the number of funded start-ups in the last decade in a start-up's country). Participation × ln(No. funded start-ups) is the interaction term between the binary treatment indicator (accelerator participation) and the logged ecosystem maturity measure. Coefficients for estimation of H2. Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 11: Estimated effect of ecosystem interaction on funding amounts (H2) for alternative specifications

Specification	ln(Investment amount)	ln(Grant amount)
Baseline	0.85** (0.35)	0.02 (0.34)
Trimmed sample	0.84** (0.35)	0.07 (0.33)
PS: Logit	0.88** (0.38)	-0.12 (0.41)
Covariates: ln(No. funded agri-start-ups)	0.85* (0.43)	0.03 (0.38)

Note: OLS coefficients for ecosystem interaction participation × ln(No. funded start-ups). For row covariates: ln(No. funded agri-start-ups, the interaction term is participation × ln(No. funded agri-start-ups). Standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

S5 Pseudo outcome analysis

In this section, to further probe the plausibility of unconfoundedness which underlies our identification strategy, we implement a pseudo outcome test in the spirit of (Imbens, 2015) for our baseline estimation. For this, we use a pseudo outcome which is a pre-treatment variable, namely, the binary indicator of having raised investment prior to acceleration. We then recompute inverse probability weights using the same procedure as in the baseline analysis, but excluding this pseudo outcome from the set of covariates targeted for balance. Using those weights, we estimate the average effect of participation on this pseudo outcome, including only the remaining covariates from the baseline specification in our IPTW estimation approach. The true coefficient of the treatment on the pre-treatment pseudo outcome variable is a priori known to be zero. Hence, if such estimate is substantially and statistically close to zero, this can be interpreted as evidence supportive of the assumption of unconfoundedness (Imbens, 2015).

The estimated coefficient of this pseudo causal effect reported in Table 12 shows that participation in the accelerator has no significant effect on the pre-treatment pseudo outcome. In other words, we observe no warning signs that a large unobserved confounder is distorting our main findings.

Table 12: Pseudo outcome analysis: Effect of treatment on pre-treatment outcomes

Pre-treatment outcome	Estimate	Std. Error	p-value
Raised investment pre SAIS	-0.22	0.58	0.70

S6 Sensitivity analysis

To assess the robustness of our treatment estimates to potential unmeasured confounding, we conduct a sensitivity analysis using the E-value framework proposed by Weele and Ding (2017). The E-value quantifies the minimum strength of association, on the risk ratio (RR) scale, that an unmeasured confounder would need to have with both the treatment and the outcome conditional on all measured covariates to fully explain away the observed treatment effect. This approach is particularly well suited to our setting, as standard sensitivity analysis tools are designed for linear models and do not directly apply to the nonlinear (logit) specifications we employ (Cinelli & Hazlett, 2020). Because our outcomes are not rare, we convert the estimated odds ratios to approximate risk ratios using the square-root transformation following (Weele & Ding, 2017) before computing E-values.

Tables 13 and 14 report the E-values for the baseline IPTW-weighted logit models of H1 and H2, respectively. Across both hypotheses, we find that an unmeasured confounder would need to be associated with both the treatment and the outcome by a risk ratio of at least approximately 1.5 to shift the 90% confidence interval of the treatment effect to include the null. That is, an unobserved variable would have to make one group of applicant start-ups roughly 50% more likely to receive treatment (i.e., be selected to the accelerator) and 50% more likely to experience the outcome, net of all observed covariates, to render the estimates statistically non-significant. To compare this threshold against observed confounding strength, we compute the approximate risk ratios that each measured covariate exhibits with both treatment assignment (from the propensity score model) and the outcomes (from the IPTW-weighted outcome models). None of our observed start-up characteristics achieves an association of this magnitude on both dimensions simultaneously. Given the generally low explanatory power of individual characteristics for early-stage venture outcomes (McKenzie & Sansone, 2019), it appears unlikely that an unobserved confounder of the required strength exists.

Moreover, substantially larger E-values would be needed to reduce the point estimates themselves to zero, further reinforcing the robustness of our findings. Taken together, these results suggest that unmeasured confounding is unlikely to account for the estimated effects of accelerator participation (H1) or the intensity of the accelerator ecosystem (H2).

The following tables report coefficients and 90% confidence intervals of our main models transformed as risk ratios. Further, the tables show the calculated E-Values (as risk ratios) for full nullification of the estimator, and for inclusion of 0 in the 90% confidence interval.

Table 13: Sensitivity analysis (H1): E-values for unmeasured confounding (90% CI)

	Dependent variable:			
	Investment	Investment>$100k	Grant	Operational
	(1)	(2)	(3)	(4)
OR	3.71	4.53	3.53	50.97
CI lower	1.27	1.23	1.22	2.95
CI upper	10.83	16.70	10.21	880.61
E-value (estimate)	3.26	3.68	3.17	13.76
E-value (CI)	1.51	1.45	1.45	2.83

Table 14: Sensitivity analysis (H2): E-values for unmeasured confounding (90% CI)

	Dependent variable:			
	Investment	Investment>$100k	Grant	Operational
	(1)	(2)	(3)	(4)
OR	2.79	1.63	0.86	2.45
CI lower	1.29	0.78	0.37	0.79
CI upper	6.07	3.42	2.01	7.57
E-value (estimate)	2.73	1.87	1.38	2.50
E-value (CI)	1.52	1.00	NA	1.00

S7 Power analysis

To assess the reliability of our estimated treatment effects, we follow the framework proposed by (Gelman & Carlin, 2014), evaluating statistical power, the risk of sign error (Type S), and effect size exaggeration (Type M). These diagnostics are particularly relevant in settings with moderate sample sizes, where significant estimates may be imprecise or misleading in terms of magnitude or direction. Following (Gelman & Carlin, 2014), we compute:

- Power: the probability of detecting a statistically significant effect at the 10% level,
- Type S error: the probability that a statistically significant estimate has the wrong sign,
- Type M error: the expected exaggeration factor among statistically significant estimates.

S7.0.1 Power analysis H1

We focus the power analysis on the effect of the accelerator participation on the probability of raising investment. For the analysis we use our sample size $n = 133$, a range of hypothetical true effect sizes (in log-odds) ranging from 0.5 to 2.5, and three scenarios for the true standard error, which are based on the observed standard error (OSE) from the baseline estimation: using the observed value, a 25% lower value, and a 25% higher value. The results are depicted in Figure 7.

For the interpretation of these results two reference values for the hypothetical true effect size are helpful which are our estimated effect of size 1.33 and a comparable estimated effect size estimated by (Gonzalez-Uribe & Leatherbee, 2018). Their value translates to approximately 1.11 log-odds when recalibrated to our baseline probability among rejected start-ups. The accelerator studied by Gonzalez-Uribe and Leatherbee (2018) is comparable in design, albeit featuring lower support intensity. Therefore, we use this as our conservative reference point jointly with the OSE scenario. At this reference point, power is 0.52; the probability of a sign error is close to zero; and the expected exaggeration factor is 1.45.

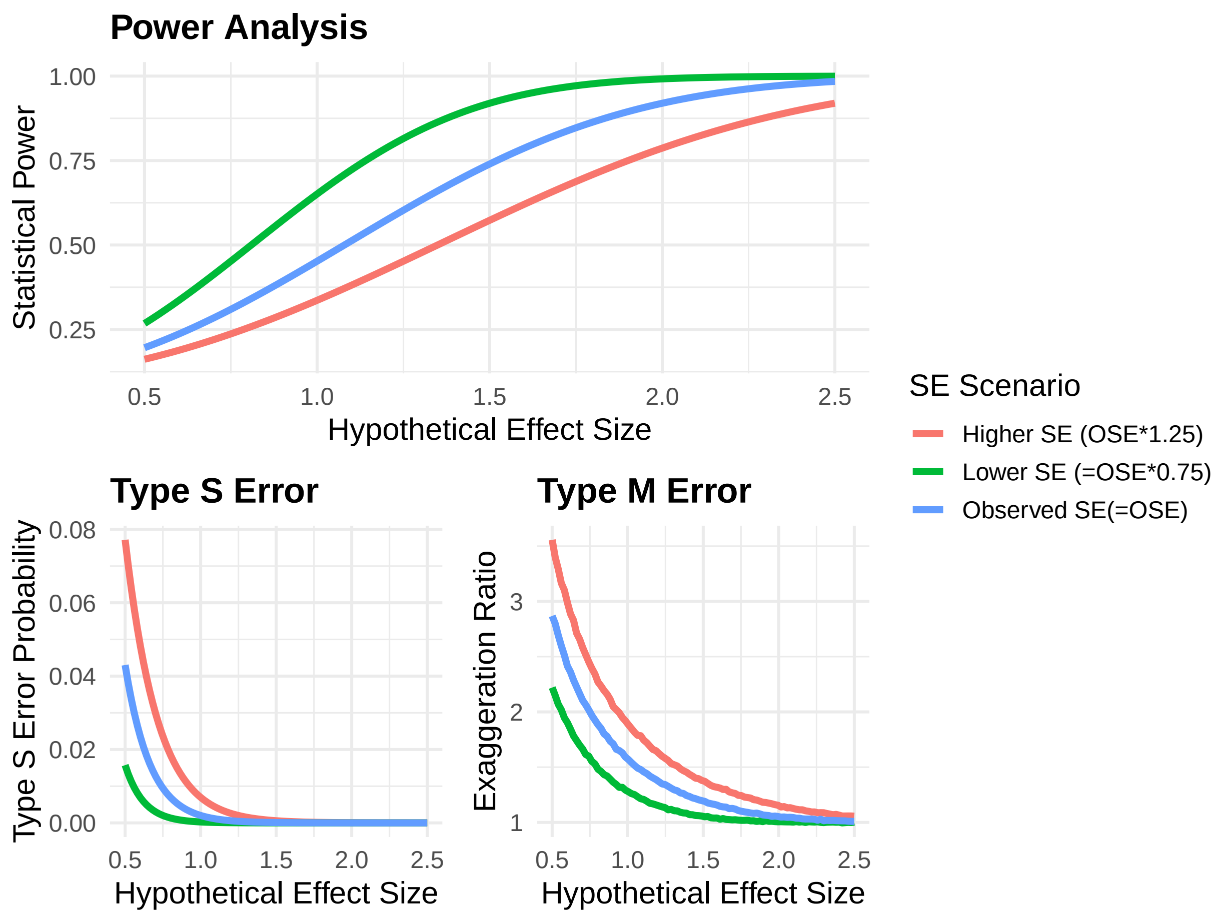

Figure 7: Power analysis for the estimation of the accelerator effect on fundraising likelihood ($n = 133$, varying true effect sizes and standard errors)

S7.0.2 Power analysis H2

Similarly, we conduct a power analysis for Hypothesis 2, focusing on the interaction term between accelerator participation and ecosystem maturity in our baseline specification. We simulate hypothetical true effect sizes between 0.5 and 2.5 in log-odds, a range that includes our estimated effect size of 0.997 for the likelihood of obtaining equity or debt financing. External reference values for such interactions are not available, as this type of moderating effect has not been evaluated in the existing literature. As before, we calculate three uncertainty scenarios based on the observed standard error (OSE) from the regression model. The results are depicted in Figure 8.

For the interpretation of these results, we use 75% of the magnitude of our estimated effect size for the influence of the interaction term on equity and debt financing as the conserva-

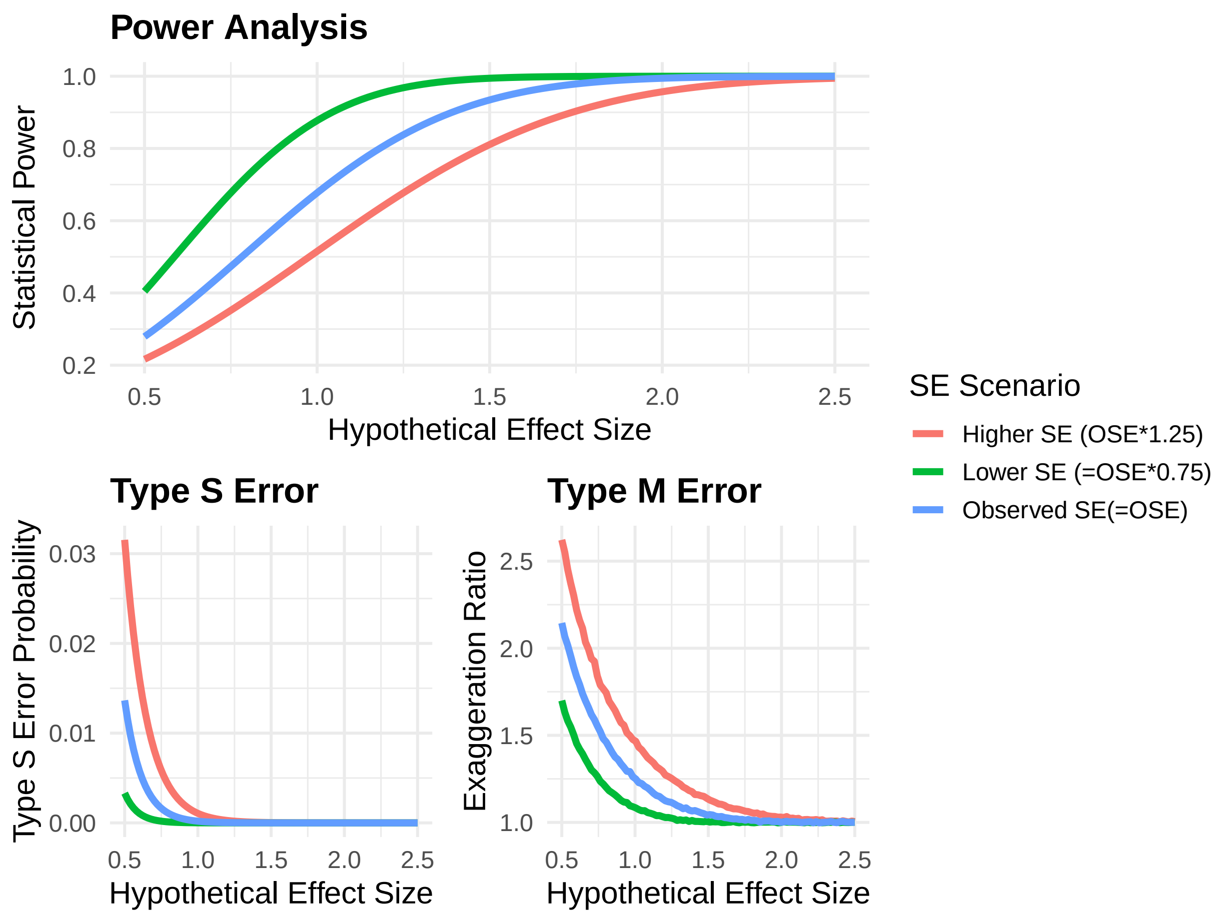

Figure 8: Power analysis for estimation of the interaction effect between accelerator participation and ecosystem maturity on fundraising likelihood, based on a sample size of $n = 133$, across varying true effect sizes and standard errors.

tive reference point jointly with our OSE scenario. At this point, power is 49%; the probability of a sign error is 0.1%; and the expected exaggeration factor is 1.49. This supports our main result of a moderation effect of the maturity of a start-up's ecosystem on an accelerator's impact on investments. Further, this highlights that the low statistical power for the analysis of H2 might constrain our ability to identify significant effects of the interaction term of participation and ecosystem maturity for outcomes beyond investment.

Therefore, in addition, we calculate the minimum effect size that our setup could reliably detect with 80% power and a 10% significance level (two-sided test), based on our sample size $n = 133$ and the estimated standard error of 0.459 for the estimated logit coefficient.

We compute this minimum detectable effect (MDE) on the log-odds scale as:

$$\text{MDE} = (z_{\alpha/2} + z_{1-\beta}) \cdot \widehat{\text{SE}} = (1.65 + 0.84) \cdot 0.46 \approx 1.14$$

Supplement references

Austin, P. C., & Stuart, E. A. (2015). Moving towards best practice when using inverse probability of treatment weighting (IPTW) using the propensity score to estimate causal treatment effects in observational studies. *Statistics in Medicine*, *34*, 3661–3679.

Cinelli, C., & Hazlett, C. (2020). Making sense of sensitivity: Extending omitted variable bias. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *82*, 39–67.

Gelman, A., & Carlin, J. (2014). Beyond power calculations: Assessing Type S (sign) and Type M (magnitude) errors. *Perspectives on Psychological Science*, *9*, 641–651.

Gonzalez-Uribe, J., & Leatherbee, M. (2018). The effects of business accelerators on venture performance: Evidence from Start-Up Chile. *The Review of Financial Studies*, *31*, 1566–1603.

Greifer, N. (2025a). Cobalt: Covariate balance tables and plots. R package version 4.6.0.

Greifer, N. (2025b). Weightit: Weighting for covariate balance in observational studies.

Ho, D. E., Imai, K., King, G., Stuart, E. A., Abadie, A., Beck, N., Cook, S., Diamond, A., Hansen, B., Imbens, G., Lau, O., Lenz, G., Rosenbaum, P., & Rubin, D. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis*, *15*, 199–236.

Imbens, G. W. (2015). Matching methods in practice: Three examples. *Journal of Human Resources*, *50*, 373–419.

Massey, F. J. (1951). The Kolmogorov-Smirnov test for goodness of fit. *Journal of the American Statistical Association*, *46*, 68–78.

McKenzie, D., & Sansone, D. (2019). Predicting entrepreneurial success is hard: Evidence from a business plan competition in Nigeria. *Journal of Development Economics*, *141*, 102369.

Weele, T. J. V. D., & Ding, P. (2017). Sensitivity analysis in observational research: Introducing the E-Value. *Annals of Internal Medicine*, *167*, 268–274.