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Entrepreneurial support organizations in the new space economy: Location, peers, and experience effects on startup performance

David Hernando-Tomé [a,*,1], Enrique Acebo [b,*,2], Julio Abad-González [a,3], José-Ángel Miguel-Dávila [b,4]

[a] Departamento de Economía y Estadística, Universidad de León, Spain
[b] Departamento de Dirección y Economía de la Empresa, Universidad de León, Spain

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ABSTRACT

Entrepreneurial support organizations (ESOs), such as incubators and accelerators, have rapidly become integral to modern entrepreneurial ecosystems. This study investigates how organizational and contextual factors affect the performance of technology startups accelerated under the European Space Agency's BIC program from 2005 to 2025. Utilizing negative binomial regression models on a dataset of 1326 European New Space startups, we examine the roles of ESO geographical location, cohort density, and institutional experience in shaping startup outcomes. Our findings indicate that: ESO geographical location significantly shapes startup employment size; accumulated ESO institutional experience is a robust predictor of startup employment growth; and cohort characteristics show secondary effects. Grounded in the Resource-Based View, these insights enhance our understanding of the value and effectiveness of ESOs in technology-intensive sectors, particularly the New Space industry.

1. Introduction

Entrepreneurial support organizations (ESOs), business incubators and accelerators, play a strategic role in the entrepreneurial ecosystem by acting as supportive entities facilitating the creation and growth of innovative new ventures. Numerous studies highlight that ESOs provide critical resources aimed at enhancing the success probabilities of startups (Hausberg & Korreck, 2021; Mian et al., 2016). Indeed, it is widely recognized that these controlled environments mitigate the challenges entrepreneurs face in early stages by bridging resource and knowledge gaps that would otherwise hinder business development (Carayannis and von Zedtwitz, 2005). Over recent decades, ESOs have evolved from their traditional role of providing mere accommodation and basic services to more comprehensive models that include specialized coaching, business planning support, investor networking, and other high value-added services (Barbero et al., 2012; Bruneel et al., 2012). This evolution reflects their growing importance as articulators within innovation ecosystems, serving as catalysts for knowledge transfer and commercialization of new technologies (Goswami et al., 2018; Hausberg & Korreck, 2021).

* Corresponding authors.
E-mail addresses: dhert@unileon.es (D. Hernando-Tomé), e.acebo@unileon.es (E. Acebo).
[1] https://orcid.org/0009-0007-1038-0763
[2] https://orcid.org/0000-0001-9022-5614
[3] https://orcid.org/0000-0002-6280-4982
[4] https://orcid.org/0000-0002-5191-0528

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Despite the wide consensus on their relevance, empirical evidence regarding ESOs, impact on startup performance has yielded mixed and nuanced results. Some studies report higher survival and growth rates among supported startups compared to ventures outside these programs (Amezcua et al., 2013; Yu, 2020). These improvements are attributed to the resource-rich and protective environments offered by ESOs, which reduce early-stage mortality and accelerate firm development (Mian et al., 2016). However, others question the universality of this positive effect, suggesting that not all ESOs achieve similar outcomes or equally benefit supported firms (Schwartz, 2011). Comparative studies similarly indicate substantial variability in startup performance depending on the type of ESO and the nature of provided support (Barbero et al., 2012). These discrepancies suggest additional contextual and organizational factors may modulate accelerator effectiveness beyond basic services.

Notwithstanding the growing recognition of ESO heterogeneity (Bergman & McMullen, 2022; Woolley & MacGregor, 2022), comparative studies have largely focused on program-level differences, incubators vs. accelerators, public vs. private, while leaving within-program variation underexplored. Yet even organizations sharing the same eligibility criteria, support structure, and governance framework may differ substantially in outcomes depending on where they are embedded, how their entrepreneurial communities are composed, and how much institutional knowledge they have accumulated over time. These three dimensions, geographical location, cohort peer density, and accumulated ESO experience, translate directly observable program characteristics into theoretically grounded mechanisms: resource access through ecosystem embeddedness (Porter, 1998; Colombo & Delmastro, 2002), social learning through cohort interaction (Cohen et al., 2019a; Hallen et al., 2020), and organizational capability through institutional maturity (Bruneel et al., 2012; Schwartz, 2012). Investigating them within a single, standardized program allows us to isolate these effects from confounds introduced by cross-program heterogeneity. The precise impact of these factors on startup outcomes is unclear: What role does location play? How do peers add value? and is ESO experience a critical determinant particularly in high-tech sectors?

One of these high-tech sectors is the space industry, which is undergoing unprecedented transformation due to the rise of the "New Space Economy". Traditionally dominated by large government agencies and contractors, the space sector now is characterized by numerous startups and private actors exploring commercial opportunities based on space technology (Abi-Fadel & Peeters, 2019), embracing agile entrepreneurs aiming to democratize space through satellite applications, micro-launchers, and geospatial data platforms, among other innovations. In this scenario, specialized space-focused ESOs play a fundamental catalytic role by facilitating entrepreneurs access to specialized technical knowledge, costly facilities or laboratories, and connections with space agencies and established industry firms. Indeed, ESOs are key agents in transferring space technology for commercial use, transforming ideas developed in scientific-technological contexts into viable businesses (Abi-Fadel & Peeters, 2019, Cavallo et al., 2025).

To boost entrepreneurship in this new sector, the European Space Agency (ESA) has established a network of ESA Business Incubation Centers (ESA BICs) across various European countries with the purpose of accelerating and incubating, exclusively supporting startups applying space technologies or satellite data in diverse markets. ESA BICs currently represent Europe's largest specialized space-focused ESO network, with over 25 centers operating in different regions and a track record of supporting more than 1800 startups over two decades (ESA, 2025). Empirical evidence substantiates the effectiveness of the ESA BIC program in fostering startup growth. Cavallo et al. (2025) demonstrate that startups supported by ESA BICs experience significantly higher growth in total assets both during and after program participation, and notably higher employment growth during the acceleration period compared to unsupported counterparts, underscoring the program's capacity to enhance startup resource endowment in the nascent space economy.

Understanding how location, peer environment, and ESO experience influence startups will help refine entrepreneurial intermediation theories and inform more effective supporting programs. Comparing ESOs is inherently challenging; however, investigating these aspects within the ESA BIC program is particularly pertinent, enabling analysis of location effects within a singular acceleration context in the emerging and distinctive space entrepreneurship landscape.

This study analyzes the performance of 1326 European new space technology startups within the ESA BIC acceleration program from 2005 to 2025. Results indicate ESOs located in regions with longstanding aerospace clusters, dense research infrastructures, and established investor communities are associated with larger startup employment. Accumulated institutional experience within ESOs substantially increases the success rates of supported startups. These findings highlight the importance of specific contextual and organizational characteristics of ESOs. The relevance of this study lies in integrating entrepreneurship, economic geography, and organizational learning perspectives to understand conditions under which ESOs add value to startups, thus addressing prior calls for examining under-studied contextual factors (Phan et al., 2005; Van Weele et al., 2017). Furthermore, this research contributes novel empirical evidence within the scarcely investigated yet economically and strategically significant space sector, providing valuable insights for public policy formulation and ESO management.

Following this introduction, Section 2 presents the theoretical framework and questions regarding location, cohort density, and experience within space-focused ESOs. Section 3 then outlines the research context. Section 4 describes the methodology, detailing the sample, data sources, and quantitative analysis. Section 5 presents empirical results concerning these factors and their impact on space startups. Section 6 discusses the findings obtained. Finally, Section 7 summarizes conclusions, theoretical and practical implications, limitations, and future research avenues.

2. Theorethical background

2.1. Entrepreneurial Support Organizations

The academic literature has increasingly recognized entrepreneurial support organizations (ESOs) as vital intermediaries within modern entrepreneurial ecosystems. The initial literature considered ESOs within the framework of mission-oriented typologies, e.g., ESOs that provide subsidized space to entrepreneurs, have a network purpose, or offer mentoring to entrepreneurs (Hackett & Dilts, 2004). ESOs have evolved in three distinct generations: while first-generation incubators having merely provided subsidized working space; second-generation ESOs have encompassed a more comprehensive set of services; and third-generation ESOs, referred to as accelerators, develop cohort-based programs of intensive mentoring and embedded educational curricula that also operate as investor networks (Bruneel et al., 2012; Mian et al., 2016).

Current typologies identify five main models of ESOs: business incubators, science and technology parks, accelerators, makerspaces, and coworking spaces, each of which provides distinct resources and services tailored to specific stages of business development (Bergman & McMullen, 2022). However, as Bergman and McMullen (2022) point out, behind the proliferation of such organizations lies the recognition of their importance, yet the diversity and multiplicity of models have generated conceptual confusion and practical overlaps that undermine their effectiveness. These authors argue that the success of ESOs depends not only on their internal capabilities, but also on the relationships they are able to foster with entrepreneurs, among entrepreneurs themselves, and with the broader ecosystem. Venture development programs act as ecosystem intermediaries through the provision of services and resources that "buffer" participating firms from external demands and uncertainty while simultaneously "bridging" entrepreneurs with infrastructure providers through network relationships and access to resources (Woolley & MacGregor, 2022).

Recent research demonstrates that organizational dynamics significantly affect the effectiveness of ESOs. The notion of “arrested development” proposed by Bergman and McMullen (2020) illustrates how unresolved tensions between competing institutional logics (such as community engagement and financial performance) can lock these organizations into rigid patterns that hinder their adaptability. Their analysis identifies six strategic decisions: space design, governance structure, resource allocation, program architecture, mentor selection, and performance metrics, where sensemaking plays a critical role in interpreting external signals and enabling adjustment (Bergman & McMullen, 2020).

At the ecosystem level, ESOs establish connections through co-opetition, that is, simultaneous relationships of cooperation and competition. In this way, the mobilization of resources and the exchange of knowledge are optimized (Theodoraki et al., 2020). Theodoraki’s empirical research in France shows that while ESOs compete for high-potential projects, they achieve higher overall performance when they collaborate in shared infrastructures and events (Theodoraki et al., 2020; Theodoraki et al., 2018). Thus, these entities operate as intermediaries that consolidate social capital and coordinate multiple stakeholders.

Despite progress, several critical gaps remain. First, no large-scale comparative analyses have been conducted across diverse geographical and institutional settings (Van Rijnsoever et al., 2017). Second, there is limited understanding of how specific design variables such as, the number of cohorts, mentor expertise, or sectoral specialization, affect outcomes (Eveleens et al., 2017). Third, evidence suggests that accumulated experience does not guarantee success without the active exercise of adaptive learning capacity (Bergman & McMullen, 2020). Fourth, there is a need to clarify under which conditions ESOs foster entrepreneurial autonomy and when they generate dependency instead (Bergman & McMullen, 2022). In addition, inconsistencies persist in the methodologies used to assess performance: much of the evaluation relies on punctual outputs (such as participant counts or funds raised) rather than sustainable outcomes (such as job creation or firm survival), which complicates both comparison and management (Schwartz, 2011; Woolley & MacGregor, 2022). According to Hausberg and Korreck (2021), most research remains biased toward successful cases, overlooking failure or constraining conditions.

Moreover, Bergman and McMullen (2022) caution that “more is not always better”: the excessive proliferation of ESOs can dilute resources and generate disorientation among entrepreneurs. They propose a research agenda focused on how these organizations should be structured and articulated within the ecosystem, raising questions regarding the appropriate number, level of specialization, and complementarities required to optimize impact. The heterogeneity in venture development program outcomes suggest that private incubators, university incubators, and accelerators each influence firm success in distinct ways, with the effect of each program varying greatly depending on the type and scope of services and resources provided (Woolley & MacGregor, 2022).

In this respect, the emerging New Space economy requires particular adjustments due to its complex regulatory framework, high capital intensity, and long development cycles (Cloitre et al., 2024). The application of the quadruple/quintuple helix model in this field underscores the necessity of integrating academic institutions, private firms, governmental bodies, civil society, and environmental considerations (Cloitre et al., 2023).

2.2. Location Research

The Resource-Based View (RBV) proposes that a firm's competitive advantages stem from its unique resources and capabilities. For startups, effectively accessing these resources is often achieved through affiliation with an ESO. Applying this perspective to ESOs, RBV suggests that an ESOs geographical location largely determines the resources available to the startups it hosts, leveraging valuable local resources, such as talent, knowledge, and contact networks, to provide location-based competitive advantages (Freire et al., 2022). An ESO situated in a resource-rich environment, characterized by access to technological infrastructure, specialized human capital, knowledge networks, and funding, can equip startups with a robust foundation of resources that are difficult to imitate. Freire et al. (2022) emphasize that resources serve as a bridge between companies and ESOs, promoting the development and sustainability of both entities.

Similarly, Bustamante et al. (2021) explore how locational considerations influence startup survival within acceleration programs. Location capabilities, defined as a firm's ability to strategically identify and exploit the potential of a specific geographical area (Khurana & Farhat, 2021), are pivotal in explaining variations in firm performance. For instance, proactive engagement in establishing relationships with key local actors can significantly enhance a firm's legitimacy, providing a competitive edge (Yang et al., 2017). This advantage is particularly notable in high-tech sectors, where firms effectively integrating and leveraging local resources exhibit higher survival rates compared to those that do not (Messeni et al., 2007; Vedula & Kim, 2019). Consequently, developing greater locational capabilities translates into increased survival probabilities and improved startup performance.

Madaleno et al. (2022) find that governmental support enhances the service capabilities of ESOs, thereby improving their performance. Initiatives such as innovation clusters, technology hubs, or state-run acceleration programs elevate local capabilities, making locations more attractive to startups. In practice, startups typically locate (or remain) where institutional support is strongest, for example, in regions offering entrepreneur funding programs, startup-friendly regulations, and government-supported mentoring networks (Chang & Cheng, 2024; Madaleno et al., 2022). A favorable institutional environment, shaped by pro-entrepreneurship public policies, constitutes a critical locational advantage influencing the development of supported startups.

Geographical location is also a crucial performance factor for supported startups in the New Space context. This setting differs from traditional technology sectors in three keyways that call for a reinterpretation of the Resource-Based View. First, the industry has a strong reliance on expensive, fixed infrastructure (launch pads, satellite integration facilities, clean rooms), which prolongs R&D cycles and raises significant barriers to entry. For this reason, it is economically advantageous to be close to shared facilities. In addition to providing resources, institutional "gatekeepers" such as ESA, national space agencies, and major aerospace primes also serve as technical knowledge validators and certification filters, establishing formalized pathways that necessitate ongoing institutional relationships (Howells, 2006).

In contrast to iterative innovation processes in service-oriented industries, these mechanisms collectively shape gradual, protocol-driven learning curves around joint missions. Therefore, being close to strategic resources (space agencies, specialized research facilities, and industrial clusters), offers significant competitive advantages by making it easier to access vital infrastructure, highly skilled labor pools, and knowledge networks unique to a given industry (Sagath et al., 2019). Nonetheless, while full replacement is still unlikely given the infrastructure-intensive nature of the aerospace industry, new data indicates that strong collaborative networks and advanced remote support capabilities made possible by digital platforms and strategic alliances can help startups situated outside of conventional aerospace hubs overcome some of their geographic limitations.

Collectively, these arguments suggest that location significantly influences startups performance. A geographically well-positioned ESO provides strategic resources (RBV) to startups and simultaneously integrates them into a supportive institutional context. The combination of valuable local resources and a favorable institutional environment may explain why an ESOs location substantially impacts startup performance and size. Building on this theoretical foundation, we examine whether location effects exist across the ESA BIC network and, if so, identify which regional contexts are associated with startup survival and larger firm size.

2.3. *Number of Peers*

From the theoretical perspective of the RBV, peers within an ESO are considered intangible resources, providing access to contact networks, tacit knowledge, informal exchanges of strategic information, and collaboration opportunities, elements that are difficult to replicate outside the specific ESO environment (Wills-Johnson, 2008). Modern ESOs typically operate through startup cohorts, groups of entrepreneurs entering and progressing together through the program within a fixed timeframe (Cohen & Hochberg, 2014; Hallen et al., 2020). This cohort-based structure fosters a collaborative learning environment where founders engage intensively with one another, generating peer effects that can significantly influence each startups performance (Avnimelech et al., 2025; Cohen et al., 2019a). Literature suggests that the quantity and quality of these peers within a cohort impact entrepreneurs learning and performance (Hasan & Koning, 2019; Wise et al., 2023). Having a sufficient group of simultaneous startups promotes collaboration, experience sharing, and a shared identity among founders (Wise et al., 2023).

In this sense, Boone et al. (2024) illustrate that colocation within an industry facilitates intraindustry knowledge diffusion, reducing information asymmetries and improving stock price information. Starting the program simultaneously and facing similar challenges tends to forge strong bonds and an uncommon sense of community among cohort entrepreneurs, resulting in mutual emotional and cognitive support (Becker et al., 2024; Bouncken & Aslam, 2019). Smith et al. (2015) find robust evidence of a cohort effect in accelerators, conferring significant networking and advisory benefits to startups and signaling credibility to external stakeholders. Participation in a high-quality cohort can therefore increase a startups visibility and credibility, for instance, among investors (Hallen et al., 2020), while founders benefit from collective knowledge and peer feedback (Becker et al., 2024). Essentially, peers act as sources of practical learning and idea validation: by comparing their progress and strategies with other startups, entrepreneurs can identify best practices and avoid mistakes, accelerating their development (Smith et al., 2015).

However, the number of startups in a cohort can have dual effects on this peer-learning process. A larger number of peers broadens the diversity of perspectives and potential networking connections available to each founder. Yet, excessively large cohorts may hinder close interaction and group cohesion. Comparative studies of accelerators reveal notable differences in cohort size and resulting dynamics (Cohen et al., 2019a). This contrast suggests that ESOs with smaller cohorts foster stronger community cohesion and more intense peer learning, whereas larger cohorts offer broader networking opportunities and greater validation scope but less frequent interactions per startup pair. Practically, both approaches have merits: smaller cohorts maximize depth in peer-to-peer relationships, and larger cohorts maximize diversity and networking opportunities. Therefore, the optimal design may depend on the ESOs objectives and how it balances interaction quality against the quantity of available connections (Cohen & Hochberg, 2014; Cohen et al., 2019a). Regardless, entrepreneurs are significantly influenced by their cohort peers, learning from their successes and failures, making peer effects a central component of startup success in acceleration programs (Avnimelech et al., 2025; Hallen et al., 2020).

From a RBV perspective, this tension can be understood as a potential resource dilution effect, as cohort density increases beyond a critical threshold, the fixed stock of mentoring hours, specialized facilities, investor attention and program staff becomes progressively shared among a larger number of competing ventures. Unlike knowledge spillovers, these tangible and semi-tangible resources are finite. This resource dilution mechanism predicts a non-linear, inverted-U relationship between cohort density and startup performance, peer-learning benefits dominate at low-to-moderate densities, while resource competition becomes the binding constraint at high densities (Wise et al., 2023).

Specialized space-sector ESOs offer homogeneous cohorts of startups generating potent peer effects. Being part of a cohort exclusively composed of space startups enables entrepreneurs to share similar technical challenges and learn from one another in real-time, fostering unique collaborative learning. Empirical evidence indicates that collaboration among co-accelerated startups enhances their technological and market knowledge (Rubin et al., 2015). Moreover, colocation in a specialized physical environment facilitates joint innovative solution development, leveraging proximity to key space infrastructure and centers. For example, proximity to European Space Research and Technology Centre provides direct access to specialized technical knowledge, deepening entrepreneurs understanding of new space technologies. This access is crucial in space-focused ESOs, where collaboration and connections to advanced infrastructures are foundational for innovative startup development (Abi-Fadel & Peeters, 2019).

Collectively, the arguments above suggest ESO managers should carefully consider the size of each cohort, as this influences collaborative learning dynamics and ultimately the entrepreneurial outcomes of participating startups (Cohen et al., 2019a; Wise et al., 2023). Accordingly, we analyze how the number of peers within space-sector acceleration cohorts affects the performance of supported startups, given the theoretical tension between positive peer learning effects and potential resource dilution in larger cohorts.

2.4. Expertise of the entrepreneurial support organizations

The RBV framework emphasizes the strategic value of accumulated ESO experience as an intangible institutional resource that enhances the performance of hosted startups, significantly influencing their overall outcomes (Kristandl & Bontis, 2007). As an ESO builds its track record, it develops best practices, organizational knowledge, and an extensive network of contacts, which can be transferred to emerging ventures under its guidance. This institutional expertise includes lessons from prior acceleration cycles, a deep understanding of entrepreneurial needs, and connections forged with key ecosystem actors (Cohen & Hochberg, 2014). Thus, mature ESOs act as repositories of knowledge and social capital that would otherwise take startups years to establish, offering valuable shortcuts to resources, information, and strategic allies (Eveleens et al., 2017). Indeed, entrepreneurs involved with ESOs learn to value intangible resources, such as knowledge, advisory support, and mentor networks, more highly than tangible assets, indicating an experience-driven learning process (Van Rijnsoever et al., 2017). Consequently, the history of an ESO generates transferable knowledge and relational ties, translating into competitive advantages for supported startups, facilitating their market growth and survival (Eveleens et al., 2017).

A fundamental mechanism through which institutional experience benefits startups is social learning within the ESO, particularly through interactions with mentors and peers. Established accelerators usually have experienced mentor networks, often veteran entrepreneurs or sector specialists, whose guidance accelerates the acquisition of entrepreneurial knowledge for novice founders. In acceleration contexts, entrepreneurs learn from formal mentor advice, creating a community of practice where experiences and solutions are shared (Assenova, 2020; Cohen et al., 2019a). This learning enhances the collaborative atmosphere of the ESO, helping entrepreneurial teams avoid common mistakes and iterate rapidly on their business models. Quality mentorship from experienced ESOs has demonstrably positive effects on subsequent firm performance, for instance, assigning highly skilled mentors correlates with significant revenue and profitability improvements in startups after one year (Assenova, 2020).

Beyond their role as learning hubs, experienced ESOs also function institutionally as bridges connecting entrepreneurs to the broader business ecosystem. Over time, ESOs establish trusted and collaborative relationships with investors, corporations, universities, local governments, and other entrepreneurial actors. Through this intermediary position, established ESOs effectively connect startups with funding sources, industry partners, specialized service providers, and even initial clients, thereby reducing information and credibility gaps. Prior studies highlight ESOs role as network brokers, facilitating startups access to contacts and opportunities otherwise difficult to reach at early stages (Eveleens et al., 2017). In practice, association with a reputable ESO enhances startup legitimacy among external stakeholders (Cohen et al., 2019a). In fact, investors and strategic partners typically trust startups supported by institutions with proven track records, improving their funding and market entry prospects. Thus, institutional reputation acquired through experience becomes transferable: startups inherit some of the ESOs credibility and relationships, facilitating smoother integration into the entrepreneurial ecosystem. Additionally, veteran ESOs typically build strategic alliances with educational institutions, angel investors, international accelerators, and others, expanding the resources available to their startups (Van Rijnsoever et al., 2017).

Accumulated experience also strengthens internal ESO capabilities crucial for entrepreneurial support, such as project selection, effective mentoring, external stakeholder engagement, and entrepreneurial skills development. Over time, ESOs refine their selection criteria, identifying traits of high-potential teams and projects, leading to increasingly high-quality startup cohorts. This discernment capability is informed by feedback from previous startup generations and market responses, enabling ESOs to focus resources on initiatives with the highest success potential. Similarly, experienced ESOs optimize mentorship processes, training management teams and mentors to provide more effective, personalized support.

Previous literature suggests that professional diversity within ESO management teams positively contributes to supported startups performance by providing broad knowledge in management, technology, and markets (Fukugawa, 2018). Indeed, having directors and mentors who have experienced multiple acceleration cycles or come from various industries enriches the guidance provided and fosters innovative solutions to entrepreneurial challenges.

Taken together, accumulated experience significantly impacts startup performance, primarily by providing a sophisticated, resource-rich support environment. Accelerators with extensive histories transfer not only technical and managerial knowledge but also an entrepreneurial culture shaped by collective learning, resulting in startups better prepared to face uncertainty. Although not all effects are immediate and some evaluations indicate long-term materialization of acceleration benefits (Lukeš et al., 2019), literature consensus confirms that experienced ESOs offer distinct advantages in terms of business growth and survival. These advantages are particularly significant for entrepreneurs with limited prior experience, who intensively leverage available mentorship, networks, and institutional know-how (Assenova, 2020).

In the New Space, accumulated institutional experience in specialized ESOs positively impacts startup performance, in terms of revenue and employment growth rates, underscoring their strategic importance in the emerging space economy (Abi-Fadel & Peeters, 2019). Superior performance is largely driven by specialized, high-quality mentorship, which has significantly boosted revenue and profitability for supported startups (Assenova, 2020). Moreover, experienced ESOs facilitate access to strategic networks, providing crucial intangible resources such as specialized knowledge and institutional legitimacy (Eveleens et al., 2017), strengthening their reputation and ecosystem connectivity. Finally, organizational learning within these ESOs mediates internal and external networks, improving business performance (Wu et al., 2021).

In brief, accumulated ESO experience translates into institutional expertise, robust mentoring programs, extensive connections, and enhanced reputation, collectively catalyzing startup learning and development, increasing their success potential within todays competitive ecosystem. We examine whether ESA BICs with longer operational histories, deliver superior employment growth outcomes for their incubatees compared to more recently established centers.

3. Research context

3.1. The New Space Economy

The space industry has experienced significant changes in the last twenty years in terms of governance, financing, technology, and strategic goals (Fey & Peeters, 2025; Golkar & Salado, 2020). It has gone from being mostly run by the government to being more commercialized and driven by entrepreneurs. This new way of operating, which is often called the "New Space Economy," is a big change from how space activities have been done in the past.

Although the term "New Space" is still somewhat controversial in academic circles, with scholars recognizing its "blurry" nature and overlapping definitions (Golkar & Salado, 2020), there is a growing agreement on what makes it unique. Golkar and Salado (2020) conducted expert surveys with professionals from the space industry, academics, and investors to find three main differences between New Space and traditional commercial space activities: (1) a strong focus on customers and the market, (2) the use of agile product development methods instead of traditional systems engineering methods, and (3) business models that are very different from those used in traditional space activities, with a focus on private capital sources, especially venture capital and private equity, instead of government funding.

The temporal origins of New Space can be traced to the early 2000s, coinciding with pivotal policy interventions and technological breakthroughs that collectively enabled private sector participation at unprecedented scales (Vernile, 2018). The launch of NASA's Commercial Orbital Transportation Services (COTS) program in 2006 is widely seen as a turning point. It brought in new ways for the government to buy things that shifted risk and ownership to private contractors while lowering strict technical requirements (Melamed et al., 2024; Vernile, 2018). This model brought in enough money to get private investors interested, which led to companies like SpaceX developing launch systems that were commercially viable and made it much cheaper to get to Low Earth Orbit (LEO) by using reusable rocket technologies (Fey & Peeters, 2025; Fiore & Elvis, 2025).

The economic scope of New Space activities encompasses the entire space value chain, including upstream segments like launch services, satellite manufacturing, and in-orbit infrastructure, as well as downstream applications such as Earth observation analytics, satellite communications, and positioning services (OECD, 2022; Orlova et al., 2020). The OECD Handbook on Measuring the Space Economy defines the space economy as "the full range of activities and the use of resources that create value and benefits to human beings in the course of exploring, researching, understanding, managing, and utilizing space" (OECD, 2022).

The way private investors are putting their money into the sector shows how quickly it is growing and how it is changing. The architecture of the funding ecosystem varies significantly by region, demonstrating distinct models of public-private collaboration. In 2024, private consortia provided more than 80% of the funding in North America. Public support mainly came in the form of big procurement contracts that made money for private investors (ESPI, 2025). In contrast, European and Asian space projects have a lot more public sector involvement through direct co-investment. For example, mixed public-private consortia made up about 80% of European space company funding in 2024 (ESPI, 2025). This pattern reflects not only differences in risk appetite among private investors but also distinct strategic approaches to industrial policy, with European institutions actively deploying capital to catalyze ecosystem development (Moranta & Donati, 2020).

The New Space is not just a gradual commercialization of current space activities, which has been happening since the sector started. Instead, it is a major change in the goals and management of space missions (Golkar & Salado, 2020). In contrast to traditional space programs, which put the needs of society, scientific progress, and national security first, New Space ventures put the needs of shareholders and return on investment first (Golkar & Salado, 2020). This shift has big effects on how engineers work. New Space companies are more willing to take risks, have shorter development cycles, and lower unit costs because they can take advantage of economies of scale. They are also more willing to accept technical failures as a cost of quick iteration (Peeters, 2024).

The macroeconomic significance of this transformation is substantial, driven by mass-market applications including global broadband connectivity via mega-constellations, commercial remote sensing, and space-based services addressing terrestrial challenges such as climate monitoring and precision agriculture (Zitelmann, 2025). However, realizing this potential remains contingent on sustained technological innovation, regulatory adaptation to accommodate novel activities, and continued public sector support, whether through procurement guarantees, co-investment, or infrastructure provision (Gonzalez, 2023).

3.2. The ESA BIC Program

The European Space Agency Business Incubation Centre (ESA BIC) network is one of the largest institutional efforts in the world to promote space entrepreneurship. It was created in 2004 under ESA's Technology Transfer Program to support entrepreneurship in space-based businesses and to demonstrate the social return on investment of European space programs (Eldering & Hulsink, 2021). Initially, the program launched with a pilot incubator at ESA's European Space Research and Technology Centre (ESTEC) in Noordwijk, Netherlands, and by 2025 there were hubs in 33 different locations, in 22 ESA Participating States (ESA, 2025).

To receive support, companies must be a legally established company in an ESA participating State, be less than five years old, and demonstrate a significant connection with space. According to the OECD (2022) definitions, they can be classified into three categories: upstream startups are those that develop technology for use in space (e.g., a new satellite component or propulsion technology); downstream startups are those that use technology in terrestrial applications and businesses (e.g., precision agriculture, environmental monitoring); and technology transfer startups are those that focus on adapting existing materials or processes derived from space activity to the non-space context (e.g., medical devices, industrial processes).

Selected ventures receive holistic support across four dimensions: (1) financially, the ESA BICs offers equity-free seed funding of up to €50,000 to protect entrepreneurial autonomy and reduce moral hazard in the public sector venture selection process (Tavoletti & Cerruti, 2012); (2) technical support provides 80 h of access to ESA scientists and engineers, as well as physical access to specialized infrastructure such as cleanrooms, thermal-vacuum chambers, and ground stations for satellites, facility access that would be impossible for a fledgling venture (Sagath et al., 2019); (3) business development offers dedicated mentoring relating to business model formation, intellectual property strategy, investor readiness, and access to ESA branding which also adds legitimacy to working through the regulatory barriers in the space industry (ESA, 2025); (4) network access facilitates connections to first customers, investors, technical partners and peer learning in cohorts from across the European space ecosystem (Sagath et al., 2019).

As ESA states, "each incubation center is managed by local champions who link their ESA BIC to local industry, universities, research organizations, government, and investor communities" (ESA, 2025). This design choice has direct theoretical implications; by embedding each center in its regional ecosystem through locally appointed managers, ESA deliberately introduces geographic heterogeneity into what is otherwise a standardized program. The resources available to a startup supported by ESA BIC Bavaria, including proximity to the German aerospace cluster, access to Bavarian deep-tech investors, and connections to local university, are structurally different from those available to a startup supported by ESA BIC Ireland or ESA BIC Lazio, even though both receive the same equity-free funding, technical hours and mentoring mandate from ESA.

This institutional design, where uniform program rules coexist with locally differentiated resource environments, makes the ESA BIC network an especially appropriate setting for examining how location shapes startup outcomes within a controlled program framework. The program is uniform in eligibility criteria, and support structures, enabling comparison across locations while providing large enough distribution of geographic features across its 22 countries of operation. Furthermore, the BIC program has been operating for 20 years, providing longitudinal depth to observe cohort effects and effects by maturity; ESA also has extensive databases to track individual venture performance trajectories (Eldering, 2025). Similarly, these characteristics of space startups (high capital intensity, long-term development cycles, complex regulatory environments, and reliance on specialized infrastructure), amplify the salience of our theoretical focus: examining how geographical location, peer density, and accumulated ESO institutional experience shape startup performance.

4. Dataset, variables and empirical strategy

4.1. Dataset

Our analysis is based on a dataset that includes 1800 international technology startups that participated in the ESA BIC accelerator program between 2005 and 2025. Using the complete list of ESA-supported startups (more than 1800 companies as of early 2025), we compared each entry with Orbis Europe (Bureau van Dijk, 2024) to obtain standardized, company-specific data: year of foundation, headquarters location, sector classification, and employment metrics. This dataset was created by cross-referencing ESA BIC program records with Orbis Europe, a comprehensive business database.

The ESA BIC program targets young, innovative startups that use space technologies or satellite data for commercial applications. Consequently, our sample includes high-tech startups operating at the forefront of their respective fields. We restricted the sample to startups with complete and reliable data available in Orbis (e.g., valid incorporation dates, sector codes, and financial information), thus ensuring that each included startup met the necessary attributes for our analysis. Entities with missing key information in Orbis Europe or with duplicate entries were excluded. Additionally, a small number of companies that did not fit the startup profile, such as corporate spin-offs, were omitted. This resulted in the exclusion of 474 unmatched startups (26.3%).

This matching process yielded 1326 startups identified and verified for our final analysis sample, representing a match rate of 73.7%. Our final sample of 1326 startups covers 24 ESA BICs across 19 countries (Fig. 1). All the companies in the sample are technology-oriented and encompass sectors such as software services and information technology, aerospace and satellite applications, advanced electronics, and other high-tech industries. This sectoral composition reflects ESA BIC focus on space innovation, with many startups developing products or services in satellite navigation, Earth observation, cybersecurity, or robotics, applying space technologies to terrestrial challenges and, in some cases, adapting terrestrial solutions for use in space.

A significant portion (approximately 66%) of our sample dates from 2015 onwards, coinciding with the accelerated expansion of the ESA BIC network. Despite this growth, the core attributes of the startups remained consistent: small, young, and innovation-driven. In summary, our dataset provides a comprehensive cross-sectional analysis representative of technology startups supported by ESA

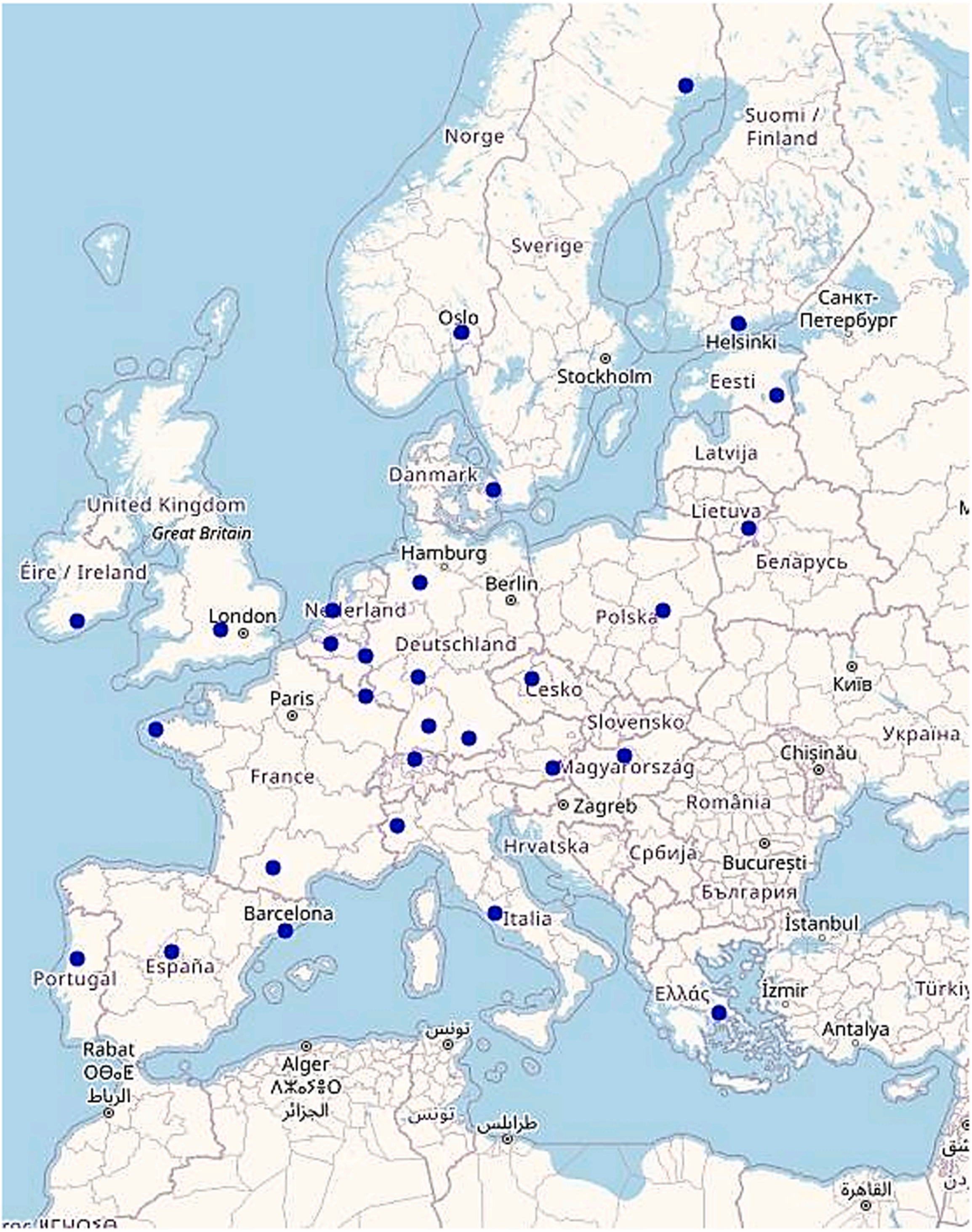

Fig. 1. Spatial distribution of ESA BIC locations. Notes: (i) ESA BIC location dummies are labelled using the official names employed by ESA, which combine national (e.g., Ireland, Poland), regional (e.g., Bavaria, Nord France, Lazio) and city-level denominations (e.g., Turin). All labels refer to the geographical area in which each ESA BIC is headquartered.

BIC, with extensive data on their backgrounds and early growth trajectories, suitable for analyzing the impact of acceleration on their development. Finally, the dataset was enriched with macroeconomic data from Eurostat and the Office for National Statistics, specifically regional-level Gross Domestic Product (GDP) according to NUTS 2 classifications.

4.2. Variables

Our study focuses on employment outcomes as a critical indicator of firm size (Coad & Hölzl, 2012). We measure firm size through the number of employees, because human resources are a central strategic asset in young, technology-intensive firms. Following Penrose's view of firms as repositories of productive services, growth in headcount reflects an expansion of organizational capacity rather than short-term fluctuations in revenues (Penrose, 2009). In the New Space sector, where ventures depend on highly specialized engineering and regulatory capabilities, adding employees is often a prerequisite for scaling complex projects and managing institutional contracts. This theoretical choice is consistent with ecosystem perspectives that treat job creation as a key outcome of entrepreneurial support (Stam, 2015; Spigel, 2017) and with empirical evidence showing that employment-based indicators are stable and robust in dynamic analyses of technology-intensive sectors (Shepherd & Wiklund, 2009; Coad et al., 2018; Cavallo et al., 2025).

Thus, the dependent variable is operationalised as the number of employees per firm reported in Orbis Europe. In our statistical analyses, this variable is treated as discrete, with each unit representing a specific employee within the firm. This approach is supported by entrepreneurial research (Canovas-Saiz et al., 2021), which highlights the importance of using employee count as a key indicator of business performance in accelerator evaluations. Treating the number of employees this way enables an effective analysis of how various factors impact startups ability to generate and sustain employment, reflecting the success and economic growth promoted by ESOs (Coad & Hölzl, 2012).

Examining organizational heterogeneity in ESA BIC effectiveness, we incorporate dummy variables for the specific ESA BIC location (each individual ESO), with Austria serving as the reference category. This specification allows investigation of whether startup employment outcomes vary systematically across ESOs, independent of startup characteristics or regional contexts. The ESA BIC dummies capture organization-specific institutional factors, including mentoring quality, network effects within each incubator, staff expertise, resource allocation strategies, and programmatic design, that shape entrepreneurial trajectories (Cohen et al., 2019b; Van Rijnsoever & Eveleens, 2021). By employing ESO-specific indicators rather than aggregated regional measures, we preserve heterogeneity at the incubator level and allow each ESA BIC to exhibit distinct employment elasticities.

To examine geographic proximity effects, we operationalize co-location using a binary indicator (Co-located) identifying startups located in the same NUT3 region as their ESA BIC. Of 1148 startups with complete location data from Orbis Europe, 367 (32%) are co-located with their ESA BIC while 781 (68%) access support from different regions. This geographic variation enables analysis of whether ESA BIC value derives from physical proximity or institutional mechanisms. We include Co-located in regression models as a control variable. The variable equals 1 if startup headquarters and ESA BIC are in the same NUT3 region, 0 otherwise. This geographic separation strengthens the interpretability of location effects, as it suggests they reflect ESA BIC institutional quality and peer networks rather than startups self-selection into resource-rich areas.

To investigate peer-related mechanisms, we operationalize peer effects using two complementary variables. First, *Peers* is the count of other startups co-located at the same ESA BIC, indicating startup density and potential for interactions, knowledge exchange, and mutual support (Cohen et al., 2019b). However, linear specifications may underestimate peer dynamics. We therefore include $Peers^2$ to test for non-linear effects. The quadratic specification allows investigation of whether peer benefits exhibit diminishing returns at high densities, that is, whether knowledge spillovers peak at intermediate concentration before competitive pressures dominate at higher peer densities. This non-linear approach reflects agglomeration theory suggesting both positive externalities (low density: spillovers) and negative externalities (high density: competition for resources). The combination of *Peers* and $Peers^2$ enables direct testing regarding optimal peer concentration.

We proxy ESA BIC institutional experience (*Expertise)* as the difference between the analysis year and each ESO's founding year (i.e., current year, founding year, based on Orbis Europe records) (Van Rijnsoever & Eveleens, 2021). This calculation yields a clear, quantitative measure of organizational age and cumulative operational tenure. While this approach ensures consistency across all 1326 startups, it does not capture variation in programmatic intensity, such as mentoring hours, budget allocations, or strategic partnerships. Accordingly, we interpret estimated effects of (*Expertise)* as indicative of organizational maturity rather than direct proxies for service quality or depth of learning.

To prevent biases in estimating ESO effects, and aligned with theoretical considerations, several control variables related to the startups themselves or their entrepreneurial environment were included. Firm-level data was sourced from the Orbis Europe database, while regional information was drawn from Eurostat and the Office for National Statistics. Specifically, the study employed the following control variables:

Startup Age, measured as the difference between the current year and the firm's registration year, controls for the natural growth associated with firm maturity (Haltiwanger et al., 2013).

The variable *Industry* captures the distribution of New Space startups across various sectors, not exclusively within high-tech industries, reflecting the diverse applications of space technologies across the economy (OECD, 2022). Startups in our sample were classified into 16 sectors covering diverse economic and productive activities. These sectors include Administrative Management, Aviation, Communications, Education and Training, Energy, Environment – Wildlife and Natural Resources, Finance – Investment and Insurance, Food and Agriculture, Health, Infrastructure and Smart Cities, Maritime and Aquatic, Materials – Manufacturing and Mining, Media – Culture and Sport, Safety and Security, Tourism, and Transport and Logistics. This classification provides a structured framework for analyzing the sectoral distribution of New Space startups and for assessing how ESA BIC support interacts with sector-specific opportunities and constraints.

Space Segments refers to the categorization of startups into three distinct technology groups, based on their use of space-derived technologies, as established by the ESA BICs. This categorical dummy variable takes one of three values: Upstream, for startups developing new technologies specifically for space applications; Technology Transfer, for startups adapting innovations initially created for space use; and Downstream, for startups primarily applying space technology to commercialize terrestrial products and services (Cavallo et al., 2025). This classification captures diverse ways space-specific technological resources are leveraged, potentially influencing employment growth.

COVID−19 Shock is a binary indicator capturing startups operational during the pandemic period (2020–2021). This variable (*COVID*) controls for potential differential impacts of the COVID−19 pandemic on startup employment trajectories. Given that ESA BIC support may have mitigated (or amplified) pandemic-related employment disruptions, including this control isolates ESO effects from exogenous macro shocks.

To approximate the economic environment surrounding each startup, *Regional GDP* captures the GDP level of the corresponding NUTS2 region at current market prices. This control accounts for differences in market size, local infrastructure, and investment climates that could independently affect firm growth (Delgado et al., 2010).

4.3. Empirical Strategy

This study employs negative binomial regression models to quantify the impact of space-focused ESOs (ESA BIC program) on the early-stage performance of technology startups. This econometric approach is appropriate since the dependent variable, the number of employees per startup, is a count variable exhibiting overdispersion (variance exceeding the mean). In such scenarios, the Poisson assumption of equality between mean and variance is violated, potentially biasing estimates if a standard Poisson regression were applied (Hilbe, 2011). When genuine overdispersion is detected in count data, alternative models such as negative binomial regression are necessary (Rothaermel, 2002). Negative binomial regression incorporates an unobserved heterogeneity parameter, adjusting variance (modeling counts as a Poisson-gamma mixture), correcting overdispersion biases, and producing consistent estimates (Cameron & Trivedi, 2013; Hilbe, 2011). This type of model is widely used for count data in entrepreneurship and innovation research and is particularly suitable for our analysis, as we measure startup performance by the number of employees, a common indicator in studies on early-stage business growth (Canovas-Saiz et al., 2021).

All specifications were estimated using Huber-White robust standard errors to address potential heteroscedasticity issues, ensuring valid statistical inference in the presence of non-constant conditional variance (White, 1980). This approach enhances the robustness of reported significance levels, providing more conservative and reliable estimates. The empirical strategy proceeds through a progressive estimation of six regression specifications, gradually incorporating additional variable blocks. This stepwise analytical construction allows us to demonstrate specific effects at each stage and assess the robustness of coefficients as additional controls are introduced.

In the initial analysis, only basic startup-level control variables (startup age, and space technology dummy variables) were included, establishing a baseline for intrinsic startup characteristics effects on employment numbers. The underlying hypothesis is that, by controlling only for age and technology, we can initially observe variations in performance. For example, it tests whether older startups already exhibit significantly higher employment than younger ones. Technology dummy variables capture any systematic differences in employment outcomes due to industry type. In the second analysis, *Regional GDP* is introduced to examine whether the broader economic environment significantly influences employment generation among supported startups.

The third analysis considers geographical differences in startup performance using ESO location dummy variables, thus capturing unobserved variables such as local policies and resource access. This analysis allows us to observe whether, after controlling for *Startup Age*, *Space Segments*, *Regional GDP*, *COVID, Co-located* and *Industry*, specific regional conditions significantly influence startup success beyond ESO support. Identifying regions with superior outcomes could reveal local ecosystems favorable to business growth, whereas areas with weaker performance highlight the need for improved support strategies. This regionalized analysis is crucial for understanding local contexts interactions with acceleration programs, informing public policies and development strategies.

The fourth analysis incorporates cohort size (the number of simultaneously accelerated startups). By introducing this variable, we assess the question related to cohort externalities. It may be that cohort size has no impact or shows either positive or negative effects. Startups in larger cohorts differ significantly in employee numbers compared to smaller cohorts. A significant positive result would support the notion that interacting with more contemporaneous startups fosters growth (peer learning/networking), whereas a negative outcome would suggest potential resource competition in larger cohorts. Thus, this analysis isolates the role of cohort dynamics in acceleration.

The fifth analysis adds the institutional experience of ESA BICs (*Expertise*). It examines whether ESOs with more experience yield better startup outcomes, whether ESA BIC experience has no effect or a positive coefficient, reflecting experiential economies. Including this variable allows comparison between startups supported by established centers versus newer ones, holding other factors constant. A significant positive coefficient for ESA BIC experience would support the idea that ESOs improve their support strategies over time, enabling their startups to achieve higher average employment numbers (Bruneel et al., 2012).

Overall, the complete model integrates all three explanatory dimensions to estimate their relative effects while controlling for relevant covariates. The full model specification is as follows:

$$Employees_{it} = f\left(\begin{array}{l} StartupAge_{it}, SpaceSegments_{it}, \mathrm{Regional}GDP_{it}, \\ Industry_{it}, Peers_{it}, COVID_{it}, Co-located_{it}, \\ Peers_{it}^2, Expertise_{it}, ESABIC_{it} \end{array}\right) \quad (1)$$

Where f(.) represents a negative binomial function estimating the number of employees for startup *i* in period *t*.

Each stage compares model performance to the preceding one, assessing the incremental contribution of newly introduced regressors (Long & Freese, 2014). All six analyses are estimated via maximum likelihood negative binomial regression with Huber-White robust standard errors. The cross-sectional sample of 1326 startups from 24 ESA BICs across 19 countries provides high statistical power and substantial geographic variation. Dynamic panel robustness checks (651 firms, 2379 observations) validate findings by controlling for firm growth trajectories and unobserved heterogeneity.

5. Results

5.1. Descriptive Statistics

The descriptive statistics presented in Table 1A provide valuable insights into the characteristics and variability of key quantitative variables related to startup performance, ESO experience, cohort dynamics, and regional economic conditions among the studied companies.

The variable *Number of employees* reveals that startups have an average of approximately 6.75 employees (SD = 14.80), yet the median of 3 indicates most startups are small, with a few larger startups significantly influencing the mean. This is further emphasized by the maximum of 290 employees, suggesting considerable variability, right skewness and the presence of outliers regarding employment size.

Regarding the variable *Startup Age*, firms have an average age of 4.31 years (SD = 3.84), with half of the startups being younger than three years. This suggests they are appropriately positioned to benefit from the ESA BIC acceleration program, underscoring the early-stage nature of most startups, possibly reflecting rapid market entry or high turnover among emerging companies.

The *Expertise* variable indicates an average ESO experience of 8.47 years (SD = 4.70), reflecting a moderate level of accumulated experience. A median of 8 years further suggests that a substantial proportion of startups benefit from ESOs with significant experience, which could positively impact their growth and resource access.

The variable *Peers* with an average of 18.13 startups and SD = 9.77, demonstrates considerable diversity in ESO cohort sizes. The observed variability, from a minimum of 1 to a maximum of 41 startups, indicates heterogeneous acceleration environments, potentially influencing collaborative opportunities and/or competitive pressures.

Finally, regional economic conditions are represented by *Regional GDP*, exhibiting considerable variability with an average GDP of approximately €160,491.76 (SD = €127,799.56) and a median near €129,102.74. This broad range, from a minimum of €4110.58 to a maximum of €860,067.30, highlights significant economic disparities between regions, which could affect the availability of local resources, investment capital, and economic incentives crucial for startup development.

To characterize the sample composition, Table 1B disaggregates employment statistics across the three phases of ESA BIC participation, using firm-level program timing data. Observations are classified as pre-support (year < incubation start year), during-support (incubation start year ≤ year ≤ incubation end year), and post-support (year > incubation end year).

A clear monotonic progression in employment is observed across phases, mean employment rises from 2.89 employees before program entry (N = 538, SD = 3.28, median = 2) to 4.06 during support (N = 1333, SD = 5.13, median = 3) and reaches 9.94 in the post-support phase (N = 1784, SD = 20.30, median = 4). Notably, 85.3% of observations with verified program dates 3117 out of 3655) correspond to the during- and post-support phases.

Additionally, Table 2 displays the Pearson correlation matrix for the main quantitative variables used in the analysis.

As expected, the number of employees is positively and significantly correlated with Startup Age ($r = 0.211$, $p < 0.001$), Expertise ($r = 0.140$, $p < 0.001$), Peers in the same incubator ($r = 0.194$, $p < 0.001$), Peers^2 ($r = 0.218$, $p < 0.001$), and Regional GDP ($r = 0.196$, $p < 0.001$). A notable moderate correlation between Startup Age and Expertise ($r = 0.383$, $p < 0.001$) suggests that older startups tend to be associated with more experienced support organizations. As expected, Peers and Peers^2 are highly correlated ($r = 0.967$, $p < 0.001$), but both are retained in the full model specification to allow for non-linear peer effects. Importantly, all other pairwise correlations remain below 0.50.

Table 1A
Descriptive statistics for quantitative variables.

Variable	N	Mean	SD	Min	P25	P50	P75	Max
No. of employees	3715	6.75	14.80	0	1	3	6	290
Startup Age	9800	4.31	3.84	0	1	3	6	24
Expertise	9225	8.47	4.70	1	5	8	12	20
No. of Peers	9160	18.13	9.77	1	10	17	25	41
Regional GDP (MIO_EUR)	7379	160,491.76	127,799.56	4110.58	73,319.07	129,102.74	224,373.20	860,067.30

Notes: (i) Observations are pooled across all firms and years.

Table 1B
Descriptive statistics by incubation phase. No. of employees.

Variable	N	Mean	SD	Median
Pre-support	538	2.89	3.28	2
During-support	1333	4.06	5.13	3
Post-support	1784	9.94	20.30	4

Notes: (i) Observations pooled across all firms and years. (ii) 60 firm-year observations excluded due to missing program entry dates.

Table 2
Pearson Correlation Matrix of Key Variables.

Variable	1	2	3	4	5	6
1 *No. of employees*	1.000					
2 *Startup Age*	0.211***	1.000				
3 *Expertise*	0.140***	0.383***	1.000			
4 *No. of Peers*	0.194***	0.000***	0.388***	1.000		
5 *No. of Peers^2*	0.218***	0.017***	0.416***	0.967***	1.000	
5 *Regional GDP*	0.196***	0.057***	0.387***	0.318***	0.366***	1.000

Notes: (i) Pearson correlation coefficients reported. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N = 1326 startups.

5.2. Regression Analysis

This section presents the results of the negative binomial regression analysis with robust standard errors (Huber-White), examining startup performance measured by employee count as the dependent variable.

Given that this is a count model, the estimated coefficients are expressed in the logarithmic scale of employee counts; therefore, to interpret their magnitude, coefficients are converted into exponential factors, allowing us to express the impact of each independent variable in terms of percentage change in expected employee numbers. Below, Table 3 shows six specifications (Models 1–6), progressively incorporating various explanatory and control variables and evaluating the statistical significance of their coefficients.

The first model, focusing on basic effects of age and technology, includes only *Startup Age* and space technology type (*Space Segments*), separated into Downstream and Upstream categories. The *Startup Age* variable shows a positive coefficient of approximately 0.143 ($p < 0.001$). This indicates that startups that are one year older have 14.3% more employees. This does not mean the startup grew 14.3%; rather, older startups tend to be larger in headcount. Additionally, the Upstream category has a positive coefficient of 0.175 ($p = 0.026$), indicating a positive effect on performance, while the Downstream category shows a negative coefficient of −0.015 ($p = 0.832$), though non-significant in comparison with the Technology Transfer category.

In the second model, which introduces a macroeconomic variable (*Regional GDP*) and sector-specific dummies, the positive impact of *Startup Age* remains significant at 0.129 ($p < 0.001$), and the GDP exhibits a robust, positive, yet small effect of 3.221 ($p < 0.001$) per million euros. This confirms that a favorable economic context positively influences growth.

The third model incorporates dummy variables for the specific locations of each ESA BIC, revealing substantial heterogeneity. We do not pre-classify ESA BIC locations as more or less mature ex ante; instead, we include a full set of center dummies and interpret ex post which locations are associated with higher or lower average employment, discussing ecosystem characteristics as post-hoc interpretations. Top-performing locations include Nord France ($\beta = 0.976$, $p < 0.001$), Bavaria ($\beta = 0.919$, $p < 0.001$), Sud France ($\beta = 0.876$, $p < 0.001$), and Baden-Württemberg ($\beta = 0.775$, $p < 0.001$). These coefficients translate to employment premiums of 115–165%, indicating that startups in these regions achieve substantially larger employment scales. These are regions that host long-standing aerospace clusters and dense entrepreneurial infrastructures, including specialized suppliers, research institutions and investor communities. These contextual features provide plausible ex-post explanations for why startups accelerated in these ESA BICs achieve systematically larger employment scales than those in locations such as Lazio shows $\beta = -0.703$ ($p < 0.001$), representing a 51% employment reduction; Turin shows $\beta = -0.892$ ($p < 0.001$), a 59% reduction; and Ireland shows $\beta = -0.408$ ($p < 0.01$), a 34% reduction. The 150 + percentage point gap between top and bottom performers underscores that ESA BIC effectiveness is geographically heterogeneous, reflecting local institutional contexts that shape startup trajectories independent of startup characteristics themselves.

A notable finding emerges regarding the COVID−19 pandemic, the *COVID* dummy variable is non-significant ($\beta = 0.064$, $p = 0.516$), indicating that ESA BIC-supported startups showed no differential employment impact during 2020–2021. This suggests institutional resilience: ESA BICs successfully buffered startups from pandemic-related employment disruptions, maintaining support continuity during macroeconomic shock.

Additionally, Model 3 introduces a co-location indicator (*Co-located*) to test whether geographic proximity between start statistically significant up and ESA BIC headquarters predicts employment outcomes. In our sample of 1148 startups with complete location data, only 32% (367 startups) are geographically co-located with their ESA BIC in the same NUT3 region; the remaining 68% (781 startups) access ESA BIC support from different regions. Importantly, the co-location coefficient is statistically non-significant ($\beta = 0.006$, $p = 0.155$), indicating that physical proximity between startup and ESA BIC does not predict employment outcomes. This finding is economically meaningful and consistent with ESA BICs operating as national innovation intermediaries rather than regional

Table 3
Binomial negative regression results explaining differences in the number of employees.

Vars	1	2	3	4	5	6
Start-Up Age	0.143***	0.129***	0.138***	0.122***	0.133***	0.129***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Space Segments						
Downstream	−0.015	−0.140*	−0.052	−0.051	−0.150*	−0.022
	(0.073)	(0.070)	(0.068)	(0.076)	(0.070)	(0.071)
Upstream	0.175*	0.299***	0.332***	0.368***	0.298***	0.305***
	(0.082)	(0.082)	(0.088)	(0.091)	(0.092)	(0.095)
Regional characteristics						
GDP (millions €)		3.221***	2.190***	2.074***	3.322***	1.781***
		(0.362)	(0.358)	(0.323)	(0.389)	(0.381)
ESO characteristics						
Peers				0.023*		0.026 +
				(0.011)		(0.013)
Peers^2						−0.001*
						(0.0003)
Expertise					−0.009	0.042***
					(0.006)	(0.012)
COVID			0.064	0.059	0.108	0.014
			(0.052)	(0.063)	(0.061)	(0.058)
Co-located			0.006	−0.107	−0.237	0.045
			(0.062)	(0.059)	(0.060)	(0.063)
Location ESABIC						
Baden-Württemberg			0.775***			0.822***
			(0.193)			(0.206)
Barcelona			0.316*			0.339 +
			(0.156)			(0.212)
Bavaria			0.919***			0.850***
			(0.129)			(0.144)
Belgium			−0.375**			−0.430*
			(0.132)			(0.170)
Czech Republic			−0.209			−0.247
			(0.216)			(0.229)
Denmark			0.152			0.313*
			(0.125)			(0.155)
Estonia			0.620***			0.693***
			(0.132)			(0.180)
Finland			0.620***			0.722***
			(0.149)			(0.161)
Hessen			−0.045			−0.341*
			(0.115)			(0.166)
Hungary			−0.321 +			−0.296
			(0.173)			(0.193)

	1	2	3	4	5	6
Ireland			−0.408**			−0.348*
			(0.136)			(0.154)
Lazio			−0.703***			−1.010***
			(0.126)			(0.199)
Madrid			−0.284*			−0.211
			(0.131)			(0.151)
Noordwijk			0.213			−0.139
			(0.194)			(0.226)
Nord France			0.976***			1.232***
			(0.109)			(0.172)
Northern Germany			0.682**			1.398***
			(0.226)			(0.257)
North Rhine-Westphalia			0.823**			1.081***
			(0.308)			(0.257)
Poland			0.845***			0.774***
			(0.228)			(0.176)
Portugal			0.111			0.049
			(0.156)			(0.169)
Sud France			0.876***			1.000***
			(0.182)			(0.207)
Sweden			−0.309*			−0.333*
			(0.120)			(0.188)
Turin			−0.892***			−0.721**
			(0.221)			(0.236)
UK			0.226*			0.047
			(0.094)			(0.120)
Industry indicators	No	Yes	Yes	Yes	Yes	Yes
p(Regional$_{characteristics}$)	-	0.000	0.000	0.000	0.000	0.000
p(ESO$_{characteristics}$)	-	-	0.000	0.000	0.000	0.000
p(Industry)	–	0.000	0.000	0.000	0.000	0.000
VIF	1.01	1.04	1.19	1.07	1.08	2.18
Observations	3715	2938	2689	2561	2804	2522

Notes: (i) All columns present results from Binomial Negative regressions with firm-specific random effects. (ii) Austria and Technology Transfer serving as a reference category for location and space segment. (iii) Standard errors, clustered at the startup level, are given in parentheses. (iv) Bottom section of the table shows p-values for joint significance tests and variance inflation factors (VIFs). (iv) + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

agglomeration hubs dependent on co-location. The value proposition of ESA BICs derives from institutional quality, curated mentoring networks, and peer composition, not from geographic proximity benefits. Critically, this lack of significance strengthens the interpretability of the location effects: the observed substantial location effects reflect ESA BIC institutional quality (regional policy environment, local entrepreneurial ecosystem maturity) rather than startups self-selection into naturally resource-rich areas.

The fourth model assesses the number of concurrently supported startups (*Peers*), testing for spillover or peer-learning effects. The linear peer coefficient is positive and statistically significant ($\beta = 0.023$, $p < 0.05$), suggesting that startups in denser ESA BIC cohorts have approximately 2.3% more employees per additional firm in cohort. This pattern is consistent with agglomeration theory: co-located startups benefit from informal mentoring networks, resource sharing, and knowledge exchange. However, this apparent peer effect requires scrutiny. A critical question emerges, does peer density itself independently predict employment, or does it proxy for unobserved ESA BIC institutional quality? When institutional variables are properly controlled in Model 6 (as shown below), the peer coefficient does not reach conventional significance thresholds ($p = 0.07$), suggesting that peer density partially reflects selection effects or unobserved institutional characteristics rather than generating independent peer-learning benefits. This nuance is explored more fully in the full specification.

The fifth model introduces institutional experience of the ESO (*Expertise*). Although the coefficient is negative, it does not reach statistical significance in this isolated model ($p = 0.148$). This may suggest that institutional experience alone shows directional effects, but its impact becomes clearer when considered alongside other variables.

Finally, the sixth comprehensive model integrates all previously analyzed variables. *Startup Age* remains robustly positive ($\beta = 0.129$, $p < 0.001$), indicating 13.8% more employees per year, the most stable predictor across specifications. Upstream technology maintains significance ($\beta = 0.305$, $p < 0.001$), while Downstream shows no differential effect ($p = 0.449$). Regional GDP remains significant ($\beta = 1.781$, $p < 0.001$), confirming macroeconomic context matters for startup scale. A critical finding emerges regarding peer effects: the linear term becomes small and no longer statistically significant ($\beta = 0.026$) while the quadratic term is negative and significant ($\beta = -0.0007$). This non-linear pattern reveals an inverted-U relationship with optimal peer concentration at approximately 19 firms per ESO (calculated as $X = -\beta_1(0.0256)/2\beta_2(-0.000677) = 18.9$). Knowledge spillovers dominate at low-moderate density, maximizing around 19 co-located startups, then declining at higher concentrations as intra-ESO competition intensifies. This precise threshold suggests ESO mentoring capacity constraints: approximately 18–20 startups simultaneously optimize peer benefits before congestion effects dominate.

Institutional experience becomes highly significant ($\beta = 0.042$, $p = 0.005$), translating to 4.3% more employees per decade of ESA BIC operation, demonstrating that experience effects require complementary institutional variables for manifestation: mature ESAs have refined mentoring, built reputation, and developed sophisticated selection mechanisms. ESA BIC location heterogeneity persists, dominating other effects: Nord France, Bavaria, and Sud France versus Lazio, Turin, and Ireland. These variations indicate geographic location is the primary institutional determinant after startup fundamentals, reflecting regional policy, venture capital availability, and ecosystem maturity.

5.3. Robustness Analysis

As a robustness check, the six model specifications were re-estimated using Poisson regression with robust Huber-White standard errors, replicating the progressive inclusion of controls and explanatory variables from Models 1 through 6. This approach relies on the quasi-Poisson maximum likelihood estimator, known for producing consistent coefficient estimates under correct specification of the conditional mean, even when the true count data distribution exhibits overdispersion. In other words, if the mean model is correctly specified, Poisson estimates remain unbiased and efficient despite overdispersion, as the robust variance captures the extra-Poisson variation. Therefore, Poisson regression with robust errors serves as an appropriate alternative to the negative binomial estimator in our analysis, ensuring the robustness of our findings.

As illustrated in Table 4, the Poisson regression results are highly consistent with those obtained previously using negative binomial models. Across all specifications, the direction and significance of key coefficients remain virtually unchanged, reinforcing the validity of the conclusions. Notably, startup age continues to exhibit a positive and significant effect on performance, indicating that older startups tend to achieve higher performance levels, consistent across both Poisson and negative binomial models. Similarly, the technology type dummy variable (Upstream) maintains the same sign and significance using the Poisson regression, confirming that startups focused on upstream space technologies consistently suggest distinct performance compared to those oriented toward Technology Transfer technologies.

The influence of the regional economic context, measured by *Regional GDP*, remains statistically significant with comparable magnitude in the Poisson specifications, confirming that higher regional economic levels positively correlate with startup performance. Additionally, the ESOs institutional experience variable (*Expertise*), a significant predictor in the negative binomial models, continues to show a positive and significant impact in Poisson models. This suggests that the beneficial effect of ESA BICs accumulated experience on current startups is robust and not sensitive to the estimation method.

Furthermore, introducing peer effects and industry dummies in intermediate Poisson models does not substantially alter key coefficients, estimates for critical variables remain stable with these controls, mirroring results from negative binomial models. Lastly, in the fully specified Model 6, the Poisson estimator yields results consistent with the negative binomial model: ESO-specific coefficients and their significance remain highly similar across both estimators.

This robustness enhances confidence in the startup performance analysis, as the primary conclusions hold irrespective of using a Poisson or negative binomial model. Thus, the identified positive effects (such as the role of institutional experience and regional context) and observed patterns can be considered reliable and insensitive to statistical assumptions regarding the underlying

Table 4
Poisson regression results explaining differences in the number of employees.

Vars	1	2	3	4	5	6		1	2	3	4	5	6
Start-Up Age	0.116*** (0.012)	0.102*** (0.001)	0.119*** (0.009)	0.096*** (0.008)	0.100*** (0.009)	0.111*** (0.010)	Ireland			−0.578*** (0.161)			−0.491** (0.172)
Space Segments													
Downstream	0.052 (0.080)	−0.044 (0.085)	0.049 (0.090)	0.079 (0.087)	−0.023 (0.090)	0.093 (0.088)	Lazio			−0.809*** (0.165)			−1.076*** (0.270)
Upstream	0.322* (0.131)	0.462*** (0.128)	0.447*** (0.117)	0.478*** (0.105)	0.466*** (0.140)	0.437*** (0.120)	Madrid			−0.343* (0.171)			−0.221 (0.220)
Regional characteristics													
GDP (millions €)		3.797*** (0.465)	2.572*** (0.487)	2.568*** (0.340)	3.822*** (0.468)	2.260*** (0.514)	Noordwijk			−0.128 (0.282)			−0.447 (0.286)
ESO characteristics													
Peers				0.007* (0.014)		0.036 + (0.021)	Nord France			0.884*** (0.130)			1.096*** (0.206)
Peers^2						−0.001* (0.0001)	Northern Germany			0.753** (0.255)			1.149*** (0.331)
Expertise					−0.001 (0.008)	0.041* (0.020)	North Rhine-Westphalia			1.021*** (0.298)			1.503*** (0.296)
COVID			0.068 (0.079)	0.087 (0.084)	0.126 (0.085)	0.012 (0.083)	Poland			0.935*** (0.236)			0.999*** (0.178)
Co-located			−0.168 (0.089)	−0.221 (0.073)	−0.368 (0.076)	−0.122 (0.091)	Portugal			0.253 (0.208)			0.265 (0.240)
Location ESABIC													
Baden-Württemberg			0.547* (0.222)			0.642** (0.234)	Sud France			0.707*** (0.181)			0.797*** (0.188)
Barcelona			0.488* (0.189)			0.584* (0.259)	Sweden			−0.244 + (0.144)			−0.234 (0.270)
Bavaria			0.921*** (0.157)			0.815*** (0.178)	Turin			−1.055*** (0.277)			−0.850*** (0.283)
Belgium			−0.290 + (0.159)			−0.243 (0.142)	UK			0.335** (0.113)			0.140 (0.128)
Czech Republic			−0.076 (0.204)			−0.085 (0.210)	Industry indicators	No	Yes	Yes	Yes	Yes	Yes
Denmark			0.191 (0.146)			0.373* (0.152)	p(Regional$_{characteristics}$)	-	0.000	0.000	0.000	0.000	0.000
Estonia			0.560*** (0.167)			0.695*** (0.200)	p(ESO$_{characteristics}$)	-	-	0.000	0.000	0.000	0.000
Finland			0.638*** (0.136)			0.846*** (0.186)	p(Industry)	–	0.000	0.000	0.000	0.000	0.000
Hessen			0.032 (0.144)			−0.268 (0.160)	VIF	1.01	1.04	1.19	1.07	1.08	2.18
Hungary			−0.455* (0.189)			−0.339 (0.210)	Observations	3715	2938	2689	2561	2804	2522

Notes: (i) All columns present results from Poisson regressions with firm-specific random effects. (ii) Austria and Technology Transfer serving as a reference category for location and space segment. (iii) Standard errors, clustered at the startup level, are given in parentheses. (iv) Bottom section of the table shows p-values for joint significance tests and variance inflation factors (VIFs). (iv) + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

distribution of count data.

In summary, Poisson regressions with robust standard errors confirm the solidity of previous results. The fact that all essential variables retain their effects, both in terms of direction and statistical significance, under an alternative count model provides strong evidence that findings are not artifacts of model selection. Consistent with prior literature emphasizing equivalence between Poisson estimates (with robust variance) and negative binomial results in well-specified models, our analysis finds no substantive changes in inferences when switching estimators. Collectively, the consistency between both estimation approaches strengthens the credibility of the results.

5.4. Complementary Dynamic Analysis: Panel Growth Model

To address the methodological challenges of model specification in longitudinal analysis and to generate credible evidence on growth dynamics, we utilized a dynamic panel model that directly accounts for how ESA BIC institutional experience and peer cohort effects impact employment growth rates rather than employment levels. Specifically, we estimate a fixed-effects panel model in which the dependent variable is the log change in employment between consecutive years and the key regressors are lagged employment, ESA BIC institutional experience (*Expertise*), and cohort density (*Peers, Peers²*). Unlike the canonical dynamic panel setting, in which the lagged dependent variable itself is the main regressor and generates dynamic panel bias, our specification explains current employment growth as a function of lagged employment levels and institutional characteristics that are not identical constructs to the dependent variable. This substantially reduces concerns about dynamic panel bias and makes the within fixed-effects estimator an appropriate and sufficient choice, as it controls for all time-invariant firm heterogeneity while exploiting within-firm variation over time (Wooldridge, 2010).[1] We therefore present results from the fixed effects dynamic specification as our primary dynamic model.

We estimated a dynamic panel data model with individual fixed effects (within estimator):

$$Growthlog_{it} = \beta_0 + \beta_{1\log\_employees\_lag_{it-1}} + \beta_{2Expertise_{it}} + \beta_{3Peers_{it}} + \beta_{4Peers^2_{it}} + \alpha + \varepsilon_{it}$$

Where *Growthlog* represents the logarithmic change in employees between consecutive periods for startup i in year t, calculated as: $Growthlog_{it} = \log(employees_{it} + 1) - \log(employees_{it-1} + 1)$. The lagged size variable captures convergence dynamics, allowing the model to identify mean reversion processes characteristic of firm growth. This dynamic specification directly addresses conceptual limitations in static models by evaluating "how fast firms grow" rather than merely "how large they are." This specification also accounts for the two institutional dimensions identified in the cross-sectional analysis: the accumulated expertise of the ESA BIC center (measured as years of ESO operation) and the density of peers (the number of co-accelerated startups within each cohort), operationalized through the *Peers* variable representing cohort size effects.

Dynamic panel analysis requires consecutive longitudinal observations by individual firm, and therefore results in lower sample size than cross-sectional analysis. The original sample of 1326 startups ultimately generated longitudinal data on 651 startups, resulting in 2379 observations. Sample reduction is characteristic and expected in studies of young startups (Sedláček & Sterk, 2017), where employment data continuity is interrupted by high firm volatility, discontinuous financial reporting, and data gaps when firms exit the market challenges particularly acute in the New Space sector and among private technology companies. Despite this reduction, the resultant dataset provides adequate temporal and cross-sectional variance for robust econometric estimation, which is notably important in this context given sector-specific data limitations.

The statistically significant coefficient on lagged size ($\beta = -0.507$, $p < 0.001$) provides robust evidence of mean reversion and convergence in firm growth. This pattern reflects both market constraints faced by larger firms and natural maturation dynamics, as expanding firms stabilize operations and encounter increased regulatory and competitive pressures. This finding aligns with sector-specific growth patterns where firms achieving substantial scale tend to consolidate rather than continue rapid expansion.

Accumulated ESA BIC *expertise* is a strong and very important predictor of employment growth ($\beta = 0.032$, $p < 0.001$). Through this relationship, each one-year increase in ESA BIC operational experience equates to an estimated 3.2% increase in relative annual employment growth rate. This effect size is again nearly identical to the cross-sectional analysis ($\beta = 0.042$, Table 3), suggesting that the effect of institutional experience is robust to econometric specifications that are fundamentally different, either static (cross-sectional levels) or dynamic (longitudinal growth rates). Hence, accumulated ESO expertise contributes to superior mentorship networks, enhanced selection practices, and improved connectivity in the ecosystem that leads to faster growth trajectories for employers.

The cohort density variables (*Peers* and *Peers²*) displays small coefficients ($\beta = 0.0140$ and $\beta = -0.0081$) that fail to reach a level of statistical significance in the dynamic specification. This changed relationship compared to the cross-sectional model reveals that while larger cohorts may be associated with a higher start-up level of employment, the influence of cohort density on the dynamic of employment growth is very low while controlling for temporal persistence and convergence dynamics. This suggests that the apparent peer effect in cross-sectional analysis likely reflects the omission of other factors.

[1] As an additional robustness check, we explored an Arellano–Bond GMM specification (Bertoni et al., 2011), but the instrument matrix was consistently singular across all lag structures tested, reflecting the short time series per firm (median T = 4 years), high firm entry/exit rates, and limited within-firm variation typical of young New Space startups conditions under which GMM is known to perform poorly (Roodman, 2009).

Table 5
Dynamic Panel Model: Determinants of Employment Growth.

Variable	Coefficient	Std. Error	t-value
1 Log _employees_lag	−0.507***	0.018	−27.92
2 *Expertise*	0.032***	0.005	5.72
3 *No. of Peers*	0.014	0.022	0.63
4 *No. of Peers*^{2}	−0.008	0.010	−0.87
F-statistic	273.13***		
N (startups)	651		
N (obs.)	2379		

Notes: (i) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6. Discussion

This study reveals significant findings regarding the impact of ESA BICs geographical location on supported startups performance, measured by employee numbers. From the RBV perspective, ESO location can be considered a strategic resource contributing directly to startup performance. In the context of technology startups, the geographical location of an ESO can provide intangible resources difficult to replicate elsewhere. The findings indicate that a startups ability to develop capabilities leveraging local resources within the acceleration environment correlates with better outcomes. This suggests that startups embedded in ESOs located in advanced regions benefit from absorbing beneficial local knowledge, norms, and practices, enhancing their growth and survival probabilities (Bustamante et al., 2021; Guzman & Stern, 2015).

The significant heterogeneity in startup employment across ESA BIC locations is consistent with the resource-based view's prediction that geographically embedded resources (specialized talent, aerospace infrastructure, investor networks) constitute difficult-to-imitate advantages (Porter, 1998; Colombo & Delmastro, 2002). Notably, the magnitude of these differences exceeds what regional GDP alone can explain, suggesting that ESO-specific ecosystem embeddedness, rather than general regional prosperity, is the operative mechanism. Our findings suggest that the spatial location of ESOs significantly affects supported startup performance. The observed differences in employee numbers by acceleration site highlight the role of the local institutional environment as a strategic resource. ESOs situated in regions with superior resources, infrastructure, and ecosystem support provide startups with tangible growth advantages, whereas less favorable locations may constrain development. Specifically, Startups in leading regions like Germany or France achieve substantially larger employment scales compared to Italy and Ireland. Therefore, ESO spatial location matters considerably, acting as a differentiating factor for performance by influencing startups access to critical environmental resources, networking capabilities, and sustained growth potential (Bustamante et al., 2021; Delgado et al., 2010). Thus, location emerges as a strategic institutional resource significantly affecting the success and scale of technology startups supported within the space sector.

The inverted-U relationship between cohort density and employment is consistent with theoretical arguments that peers simultaneously act as learning resources and as competitors for scarce mentoring capacity (Cohen et al., 2019a; Hallen et al., 2020). The non-significance of aggregate peer count in the fully specified model (Model 6) suggests that quantity-based peer measures are insufficient proxies for the peer-learning mechanisms theorized in Section 2.3, consistent with Bergman and McMullen's (2022) caution that more is not always better in ESO design. We find evidence that Peer effects in ESO environments exhibit robust non-linear dynamics. Linear specifications suggest positive effects; however, allowing quadratic terms reveals inverted-U relationship with employment maximized at approximately 19 firms per ESO. Economically, this threshold reflects ESO mentoring team capacity constraints, below 19 firms, knowledge spillovers and informal networks remain underutilized, generating weak positive marginal effects; beyond this point, intra-ESO competition for mentoring attention, talent acquisition, and market opportunities intensifies, creating negative externalities that offset spillover benefits. This inverted-U pattern persists in comprehensive specifications confirming genuine peer mechanisms rather than spurious correlation from omitted variables. The precise optimum (19 startups) suggests ESO policy should target selective portfolios balancing spillover benefits against coordination costs, rather than pursuing quantity-maximization strategies common in accelerator practice.

The robust positive association between ESO institutional experience and startup employment aligns with the organizational learning mechanisms outlined in Section 2.4: experienced ESOs have refined selection criteria, deeper mentor networks, and stronger legitimacy signals to investors, intangible institutional assets that, by definition, cannot be acquired quickly (Bruneel et al., 2012; Schwartz, 2012). This result is particularly notable because it holds across both cross-sectional and dynamic specifications, ruling out the possibility that it merely reflects cohort composition differences. Our results also suggest a positive effect associated with the accumulated experience of the ESO on supported startups performance. Startups housed in more experienced space ESOs tend to have a higher average employee count, an effect statistically significant after controlling for other variables. This finding aligns with organizational learning and experience theory: as an ESO accumulates operational years, it learns from past iterations and refines its support, selection, and mentoring practices, enhancing the performance of its startups (Eveleens et al., 2017). In other words, the ESO develops dynamic organizational capabilities, such as more consolidated mentor networks, better-tailored training programs, and more efficient internal processes, which constitute valuable intangible resources benefiting current startups (Barney, 1991).

From the RBV perspective, ESO experience becomes a resource challenging for newer ESOs to replicate, including accumulated tacit knowledge, trust-based external relationships, and ecosystem reputation, all facilitating supported startups growth. This finding resonates with Eveleens et al. (2017), highlighting ESOs as network brokers increasing their capacity to provide resources and relational capital to new ventures over time. Our study suggests veteran space-focused ESOs leverage previous lessons to optimize resource allocation and mentorship, reflected in enhanced startup performance. Our empirical results support the importance of these factors, providing quantitative evidence that ESO learning curves yield positive returns for supported startups. This contributes nuance to the debate in the literature, where some studies indicated mixed outcomes regarding ESO impact on entrepreneurial performance (Eveleens et al., 2017).

7. Conclusions

This study examined why, despite operating under the same program framework, eligibility criteria and support structure, some ESA BICs consistently produce larger, more employment-intensive, startups than others. The evidence consistently points in the same direction, where an incubator is located and how long it has been operating matter far more for startup employment outcomes than the sheer number of co-located peers. These findings carry direct implications for the design and governance of the ESA BIC network.

The empirical evidence obtained in this study suggests that institutional factors play a crucial role in the performance of startups supported by ESA BICs. Specifically, the findings support the theoretical framework integrating the RBV and institutional network perspectives, demonstrating that both resources provided by the ESO and the networks and relationships in which startups are embedded significantly associate with firm size (Barney, 1991; Granovetter, 1985). Therefore, our results suggest that the institutional context of acceleration is not merely a passive environment but rather a source of competitive advantages (or constraints) for new ventures.

ESO location has a significant and heterogeneous impact on space startup performance as measured by employee numbers. Specifically, acceleration at certain space ESOs such as ESA BIC Bavaria, BadenWürttemberg, Nord France, and Sud France have larger employment headcounts on average, while startups in locations such as Turin, Lazio, and Ireland, on average, show inferior performance. This finding suggests that each ESOs regional and institutional environment provides different levels of resources and networking opportunities for startups (Bustamante et al., 2021; Delgado et al., 2010). From the RBV perspective, the advantage observed in ESOs located within regions with documented aerospace clusters and dense innovation infrastructures, may derive from the availability of valuable and difficult-to-imitate resources in those regions.

Peer density effects in ESO environments exhibit robust non-linear dynamics, with startup employment maximized at approximately 19 co-located startups per ESO. This inverted-U relationship reflects fundamental tension between knowledge spillover benefits (dominant at low-moderate density) and competitive pressures for resources (dominant at high density). Importantly, this non-linearity persists even after controlling for institutional quality variables, confirming genuine peer-learning mechanisms beyond mere selection effects. From the RBV perspective, the optimal 19-firm threshold may reflect ESO mentoring team capacity constraints a valuable, difficult to imitate organizational capability that determines maximum effective peer density (Cohen et al., 2019b).

Institutional experience of space ESOs was found to have a significant and positive effect on supported startup performance. This indicates that more established ESOs, with longer trajectories and accumulated organizational knowledge, transfer valuable intangible resources to their supported startups, such as refined management practices, experienced mentoring, and a reputation facilitating access to funding and customers (Bruneel et al., 2012). This result aligns with the idea that ESOs undergo an evolutionary process in which, over time, they integrate higher value-added services and institutional learning, thereby enhancing their ability to foster startups (Bruneel et al., 2012). From the RBV perspective, ESO experience can be considered an organizational resource providing sustainable competitive advantages to benefiting startups (Barney, 1991). Additionally, ESOs with greater experience typically have more extensive external networks with investors, corporations, and other support institutions, aligning with institutional network theories highlighting the importance of these connections for business growth (Bustamante et al., 2021).

Collectively, the presented evidence underscores that the success of supported space startups does not solely depend on their internal capabilities but is strongly influenced by the institutional and relational context in which they develop. This study contributes to the academic debate by empirically demonstrating how ESO specific factors, such as location, internal entrepreneurial community, and organizational experience, serve as sources of competitive advantage for new ventures. These findings complement traditional approaches centred on startups intrinsic resources (Barney, 1991) with a more contextual and interconnected perspective, where networks and institutions play a key role (Bøllingtoft, 2012; Granovetter, 1985). In doing so, this study responds to calls for research that moves beyond program-level comparisons to examine within-program heterogeneity (Van Rijnsoever et al., 2017; Woolley & MacGregor, 2022), and contributes to ongoing debates on how ESO design, location, and institutional learning jointly shape the entrepreneurial outcomes of supported ventures.

7.1. Theoretical Implications

Our findings reinforce an integrative approach combining resources and ecosystems to explain the performance of supported startups. The evidence suggests that successful acceleration does not depend solely on the startups intrinsic attributes but also on a range of external resources and relationships provided by the ESO and its surrounding environment. The RBV offers a lens to understand how institutional resources (experience, mentor networks, sectoral knowledge) extend startup capabilities, enabling them to overcome typical limitations faced by new ventures (Donaldson et al., 2025). Simultaneously, location capabilities and peer effects contextualize the RBV by demonstrating that these external resources yield greater benefits when embedded in favorable community and regional environments.

The results indicate that, under favorable conditions, acceleration makes a tangible difference in startup growth. This aligns with recent analyses emphasizing ESO heterogeneity and the evolution of their operational models. Advanced-generation ESOs, which incorporate intensive mentoring, investor connections, and linkages with local clusters, tend to achieve better outcomes than those providing only basic infrastructure. Similarly, this is consistent with findings from accelerators where peer interaction (up to an optimal number) and guided learning correlate positively with performance metrics.

The presented evidence strengthens the theoretical framework by integrating RBV and ecosystem theory: demonstrating that valuable resources reside not only within startups but also in their immediate surroundings, and that effectively leveraging these external resources is crucial for performance (Barney, 1991; Granovetter, 1985; Hallen et al., 2020). These insights contribute to a deeper understanding of how space-focused ESOs can enhance supported startup development, contingent upon the type and location of resources available.

7.2. Practical Implications

In practice, the results offer valuable insights for ESO managers and entrepreneurship policymakers. For ESO managers, particularly within the ESA BIC context, findings highlight two essential strategic actions: strengthening internal community interactions and developing robust institutional capabilities. Promoting frequent interactions and mutual learning among supported startups through integrated coworking spaces, collaborative workshops, and cross-mentorship between established and newer companies is crucial. Managers should actively facilitate internal networks, identify synergies among startups facing similar challenges or complementary business interests, encourage joint projects, and create environments conducive to collaboration. The evolution of ESOs from mere providers of physical space to effective network orchestrators, capable of connecting individuals and knowledge, has been shown to significantly enhance startup performance and growth.

For public policy designers, findings clearly indicate that ESO support should extend beyond infrastructure investment, substantially improving program quality and ensuring deep integration within local ecosystems. Policies should foster strong connections with universities and R&D centers, incentivize sustained mentorship programs, and facilitate active participation by experienced mentors, including at the international level. In line with Bliemel et al. (2019), it is strategically beneficial to encourage the creation and strengthening of sector-specific clusters around ESOs, attracting complementary firms, specialized suppliers, and organizing aerospace-focused events.

Beyond these operational considerations, our quantitative evidence points to three strategic priorities specifically for the governance of the ESA BIC network as a whole.

First, institutional maturity emerges as the most consistent organizational driver of startup performance: centers with longer operational histories tend to host systematically larger ventures. Rather than prioritizing the creation of new incubators in additional subnational regions, our results suggest that ESA and its Member States would obtain higher returns by deepening the capabilities and deal flow of already existing ESA BICs within each country. In practical terms, this means concentrating coordination, funding and mentoring capacity on ensuring that current centers operate at sufficient scale, for instance, by reaching a critical mass of high-potential entrepreneurs, before opening additional BICs in the same national context. This should not be interpreted as a recommendation to reduce the geographical coverage of the program or to exclude countries from the network, but as a call to avoid spreading limited resources too thinly across multiple underutilized sites.

Second, location heterogeneity within the network is large and persistent, the employment gap between the most and least productive ESA BIC locations is substantial. Rather than treating all centers as equally effective, ESA could benefit from introducing a differentiated support framework that identifies underperforming centers early, diagnoses the ecosystem factors (investor base, space infrastructure, technical talent) behind the gap, and targets capacity-building accordingly. This is not an argument for closing underperforming centers but for providing them with the support needed to address the performance gap.

Third, cohort size should be actively managed, the inverted-U pattern in peer effects suggests that neither very small nor very large cohorts are optimal. Centers operating well below 15–20 startups at a time may benefit from pooling cohorts across national or regional borders; centers consistently exceeding 25–30 active firms risk diluting the mentoring and networking benefits that make the program valuable.

Taken together, these findings suggest a reorientation of ESA BIC governance, from a model centered on breadth of coverage and uniform program delivery towards one that rewards institutional quality, deepens capabilities in the strongest centers and provides targeted support to those that underperform. After more than two decades of operations, the ESA BIC program has the empirical foundation to make that shift.

7.3. Limitations and Future Research

This research presents certain limitations that should be acknowledged, offering opportunities for future studies. First, the young nature of the startups analyzed resulted in limited availability of longitudinal data compared to mature firms. Given their short operational record, these new ventures restrict the observation of long-term effects. Consequently, the relatively short temporal scope of our dataset may have prevented the detection of delayed impacts of acceleration on performance (Schwartz, 2011). This limitation highlights the benefit of future research employing longer longitudinal designs to track startup evolution beyond ESO exit, allowing the examination of the persistence and scope of observed effects.

Moreover, from a methodological perspective, the study entails typical limitations associated with quantitative research based on secondary data. Although our regression models identify significant associations, unobserved factors may have been omitted from the analysis, posing risks of omitted-variable bias (Hackett & Dilts, 2004). Additionally, retrospective data from commercial databases might limit accurate measurement of key constructs. Regarding the dynamic panel specification, our model explains employment growth as a function of lagged employment levels and institutional characteristics that are not identical constructs to the dependent variable, which substantially reduces concerns about dynamic panel bias and makes the within fixed-effects estimator an appropriate and sufficient choice (Wooldridge, 2010). Although the within estimator cannot fully rule out time-varying unobserved confounders, it controls for all time-invariant firm heterogeneity and exploits within-firm variation consistently. Accordingly, the dynamic coefficients should be interpreted as robust associations rather than strictly effects attributable to ESO intervention, consistent with standard practice in observational panel studies of this type. Future research employing longer panels or quasi-experimental designs could enable instrumental variable strategies for stronger identification of ESO-specific effects.

Measurement of peer effects also deserves careful consideration. Our analysis specifies peer effects through aggregate cohort density, a measure that weighs institutional quantity, but not quality. The lack of significance of peer density in our comprehensive cross-sectional model (Model 6) and dynamic panel model (Table 5), compared to its tangential significance in simpler models (Model 4), indicates that this variable is a poor measure of peer-learning mechanisms. Refining the measurement of peer effects would require separating: matching on specialization (the extent to which startup technical domain overlaps with center expertise), quality of expertise network (the number of domain-specialized mentors and their level of experience), quality of industry connections (existing relationships and advisory partnerships) and the legitimacy of the institution (the ESO's reputation and standing in the ecosystem). Future studies, with a finer-grained institutional measure that differentiates peer quality from quantity, may better elucidate peer-learning mechanisms and the effects of institutional quality. This refinement is also particularly necessary in the context of the space sector's reliance on specialized expertise and technical networks.

Our primary regression specifications pool observations across pre-support, during-support, and post-exit periods. Although the descriptive analysis in Table 1B documents a clear monotonic employment progression across phases, our cross-sectional and dynamic panel models do not allow us to estimate phase-specific effects that can be confidently distinguished across phases. Consequently, our main estimates cannot distinguish whether ESO institutional experience generates stronger effects during active program participation or following program exit. This distinction carries significant theoretical and policy implications: if institutional resource provision dominates, ESO intensity and quality during support periods are critical, if organizational learning and capability internalization drive effects, post-exit alumni networks, ongoing mentoring, and institutional connections become important for sustained startup performance. Future research employing event-study designs with precise program entry/exit dates and specification of temporal heterogeneity could clarify which mechanisms drive ESO effectiveness across startup lifecycle stages.

Our analysis documents associations rather than effects that can be conclusively attributed to ESO intervention. We acknowledge three potential sources of bias. (1) ESA BICs screen startups while startups choose ESA BIC locations, making it difficult to disentangle ESO impact from startup quality selection (Double selection). (2) Resource-rich areas may independently create successful startups through venture capital concentration, university spillovers, and clustering effects, rather than through ESO intermediation. (Reverse causality) (3) Startup relocation, successful startups may relocate into better-resourced regions, creating upward bias in location effects. While we cannot fully address these with observational data, our co-location analysis (68% of startups are in different regions than their ESA BICs) and dynamic panel results (consistent with cross-sectional findings) provide partial mitigation. Future research using quasi-experimental designs or instrumental variables could provide more credible identification of ESO effects.

Furthermore, our analysis does not capture micro-level determinants of founder’s location choices, such as family ties, access to international schools, administrative flexibility in hiring, or perceived cultural and linguistic comfort with a given region. These non-tangible factors may simultaneously influence both the decision to join a particular ESA BIC and subsequent employment trajectories, representing an additional source of unobserved heterogeneity that our cross-sectional and panel specifications cannot fully address. Relatedly, although the ESA BIC program formally offers uniform equity-free seed funding, actual financial allocations may vary across centers due to local co-funding arrangements and national agency contributions, differences that our secondary dataset does not capture and that could partially explain the observed location heterogeneity in employment outcomes. Future research employing mixed-methods designs, founder-level survey data, or startup-level funding records could shed light on how these personal, contextual, and financial factors interact with institutional ESO characteristics to influence startup performance.

A related limitation concerns non co-located startups, which represent 68% of our sample and may effectively operate at the intersection of two environments: their own local ecosystem and that of the ESA BIC. Our models do not disentangle the direct effect of a startup's home region from the indirect, mediated effect of the incubator's location. Accordingly, the location coefficients in Table 3 should be interpreted as capturing combined institutional and regional influences rather than purely ESO-driven effects. Finally, at the NUTS 3 level, the co-location indicator remains a coarse proxy for true ecosystem overlap. Ecosystem boundaries do not necessarily coincide with administrative units, and two firms within the same NUTS 3 region may still face very different local resource environments depending on their precise location and sector. Future research could address this by explicitly modelling the startup's home region as an additional control or by restricting the sample to co-located ventures.

The obtained evidence and theoretical framework suggest several avenues for future research. Under the resource-based view, it would be valuable to explore how supported startups develop and sustain competitive advantages after exiting the ESO. From an organizational learning perspective, future studies could investigate how accumulated ESO experience enhances startups absorptive capacity and innovation (Argote & Miron-Spektor, 2011). Moreover, comparative studies could examine recent phenomena, such as contrasting traditional ESOs with startup accelerators, a growing model warranting further attention (Pauwels et al., 2016).

Finally, after more than two decades of operations, the ESA BIC program has generated a substantial body of institutional experience and startup performance data. The patterns documented here, the primacy of incubator experience, the large geographical heterogeneity in outcomes, and the non-linear dynamics of cohort density, suggest that the network has reached a stage where systematic reflection on its design is needed. Moving from a model centered on breadth of coverage towards one that balances geographical reach with a stronger focus on program quality, mentor depth and ecosystem integration could considerably amplify the program impact on European space entrepreneurship. We hope these findings offer a useful empirical basis for that conversation within ESA and its Member States.

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CRediT authorship contribution statement

Julio Abad-González: Writing – review & editing, Supervision, Software, Investigation, Formal analysis. **José-Ángel Miguel-Dávila:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **David Hernando-Tomé:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Enrique Acebo:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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