



Assessing the impact of seed accelerators in start-ups from emerging entrepreneurial ecosystems

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Abstract

This study provides new evidence regarding the significance of enrolling in a seed accelerator programme for the performance and prospects of startups. The main novelty and contributions of this work lie in siting the analysis within an emerging entrepreneurial ecosystem (EE) and exploring the impact of both the business model and technological levels of new ventures. We tested a set of six hypotheses through empirical analysis of a dataset comprising 735 startups located in Valencia (Spain), a region representing the category of an emerging, medium-sized EE. The findings revealed that within this EE, the advantages of being accelerated tended to diminish and were more marginal than expected. Furthermore, the seed accelerator profile appeared to be of little importance to the prospects and attractiveness of firms to investors. Interestingly, their technological levels were strongly correlated with higher investment but not with a higher number of employees. The expected direct relationship between funding and firm size was also confirmed. A particularly noteworthy finding was the direct relationship between a higher technological level and business-to-business (B2B) models, as well as the opposite relationship for business-to-consumer (B2C) models. These findings have several significant implications for management and policymakers, including the apparent lack of advantages for accelerated firms in closing large investment rounds and the recommendation that incubators prioritise new ventures with high technological capacity and focussing on B2B models. Finally, we highlight the profile of startups with strong prospects for attracting investment and scaling up.

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Introduction

The increasing number of cities and regions aspiring to establish themselves as entrepreneurial hubs has led to the emergence of numerous entrepreneurial ecosystems (EEs) that are marked by significant disparities, with these being particularly evident between more advanced and established ecosystems versus smaller, recently emerged ones. The academic literature has demonstrated that the impact, expectations, and prospects of any EE depend on their access to key factors such as educational and research institutions, a population with an entrepreneurial mindset, networking between agents, access to funding, market size, and growth (Audretsch & Belitski, 2021; Cavallo et al., 2019; World Economic Forum, 2014). Despite this, the existing literature falls short in adequately addressing the expanding diversity among EEs in terms of two of their key agents: startup companies and seed accelerators (SAs), thereby leaving a research gap unexplored.

Since 2012, the number of SAs around the world has grown. They often provide limited duration programmes aimed at helping entrepreneurs define their ideas and build their first prototypes. The first SAs appeared in the United States where most of the largest and most highly ranked SAs still have their headquarters, predominantly in the San Francisco Bay Area. However, SAs have spread globally, with Europe now home to hundreds of them. Indeed, SAs have proliferated significantly in the last 15 years to the point where they have now become essential agents within the context of EEs. However, the range of roles, orientations, and impacts of SAs depends on the development and maturity level of the EE in which they are located—a topic that has not yet been addressed in the current academic literature on EEs and SAs.

In parallel to growth in the promotion of SAs across practically every EE, several different types of SAs can now be distinguished (Lukeš et al., 2019) depending on their promoters, which can include universities, corporations, public institutions, and private agents, among others. Additionally, SAs can also vary based on their orientation and priorities regarding the profiles of their tenant firms. Overall, this diversification has resulted in a wide array of incubators and accelerators that can no longer all be considered on equal terms. However, the academic literature often portrays SAs as a homogeneous group of entities with little disparity among them. Consequently, analysis of differences in the performance of tenant firms based on the profile, approach, and priorities of their SAs, is an area that remains relatively unexplored, especially in the context of emerging EEs. Therefore, this current study aims to bridge these gaps through empirical analysis, focusing on startups and SAs operating in Valencia, a specific region of Spain that homes a medium-sized emerging EE.

Similar to the work of Van Rijnsoever and Eveleens (2021), we will investigate the factors that explain the attractiveness of new ventures to external investors and the distinctions between accelerated and non-accelerated new ventures. However, our focus will be mainly on Valencia as an emerging, medium-sized EE, which is a noteworthy departure from the predominantly mature EE-centric

studies dominating the field of study of EEs. The primary aim of this study was to identify the distinctive characteristics specific to startup and scaleup companies within emerging EEs, which likely differ from the profiles and behaviours displayed by these firms in more developed and mature ecosystems. The vast majority of studies in the literature focus on advanced EEs, resulting in findings that are incomplete and biased. Thus, our primary objective was to address the following research question: How do startups from emerging EEs perform?

Apart from answering this broad research question, this study was also designed to achieve two more specific objectives. Firstly, we aimed to provide new evidence on the impact of SAs on the growth of hosted startups, considering the profile, priorities, and orientation of the acceleration programme. We hope that the evidence generated by our empirical research will inform strategic decision-making by SAs and provide valuable insights for entrepreneurs to make well-suited and tailor-made decisions when engaging with SAs. Secondly, we aimed to identify the intrinsic factors within startups that are associated with higher rates of job creation and capital attraction within the context of emerging EEs. More specifically, we wanted to uncover the combinations of startup profiles and SA programmes most likely to promote job creation and attract capital, both of which are among the most crucial indicators of success for startup companies.

To fulfil these objectives, we conducted an extensive empirical study based on the Valencian startup ecosystem. This EE ranks third in Spain, following Madrid and Barcelona. In stark contrast to the top two hubs in the country, Valencia represents an emerging, medium-sized ecosystem that surpasses Malaga, Seville, and Bilbao in terms of the number of SAs and startups it homes. In Valencia, much like in most European EEs, several branches of international SAs, functioning almost as franchises, coexist alongside regional and local business incubators and SAs.

This study makes several contributions to the existing literature on SAs and the performance of startups. Firstly, it is novel in that it reveals the specific traits and characteristics of startups in emerging EEs and the factors that explain differences in the growth and investment attractiveness of both accelerated and non-accelerated startups. Therefore, this work expands our knowledge of startups originating and located in EEs other than the leading and mature ones. Secondly, we present a new framework for classifying SAs based on their ability to generate high-performing new ventures. Thirdly, we delve into the role and impact of specific factors that define the profile of startups in terms of their technological level and business model, an area which has been insufficiently analysed thus far.

The remainder of this article is structured as follows. The next section presents the theoretical framework. Following that, the model and variables used for the empirical analysis are introduced and our hypotheses are proposed. The subsequent section provides details of the data set, descriptive data, and statistical methodology. Next, the results are presented, followed by a discussion of these results. The final section presents our main conclusions and outlines the implications and limitations of this work.

Theoretical framework and hypotheses development

This section offers a multi-perspective review of studies on EEs currently available in the literature, the performance of SAs and their impact on incubated firms. This section also evaluates how both technological level and business model influence the prospects of a startup. At the end of the section and considering the literature review, we have formulated the hypotheses of the study. Given the fact that multiple variables can influence each hypothesis, we have created a separate section specifically to present all the hypotheses. This is because these factors, which play key roles in these hypotheses, are wide ranging and therefore deserve individualised analysis.

Entrepreneurial ecosystem dynamics

The EE is defined as a complex network of individuals, organisations, institutions, and resources that create and support entrepreneurship in a specific geographic or industry area (Stam & Van de Ven, 2019). Isenberg first introduced the concept of the EE in 2010, as “a group of interconnected entrepreneurial actors, institutions, and supporting organizations that join together to create and maintain an environment conducive to the creation and growth of new ventures” (Isenberg, 2010). An EE comprises a set of actors and factors coordinated in such a way that they enable productive entrepreneurship and competitiveness among high-tech startups within a particular territory (Stam & Spiegel, 2017).

EEs evolve over time, passing through a sequence of maturity level stages. However, given the hundreds of technological clusters present in different countries, it is difficult to identify the level of development of each ecosystem. Cukier and Kon (2018) proposed a methodology to measure this maturity with respect to multiple factors, enabling them to compare different ecosystems. According to these authors, EEs emerge and evolve over a period of time, transiting through different phases of evolution: (i) nascent, (ii) evolving, (iii) mature, and (iv) self-sustainable.

A nascent ecosystem is already recognised as a startup hub and already works with some pre-existing startups and has a few investment deals but does not have a huge output in terms of job generation or worldwide penetration. Evolving ecosystems work with a few successful companies, have some regional impact, generate jobs, and have a small local economic impact. Mature ecosystems assemble hundreds of startups, account for a considerable amount of investing deals, existing successful startups with worldwide impact, and a first generation of successful entrepreneurs who helped the ecosystem grow and become self-sustainable. Finally, self-sustainable ecosystems are home of thousands of startups and financing deals, have at least a second generation of entrepreneurial mentors, especially angel investors, a strong network of successful entrepreneurs engaged with the long-term maintenance of the ecosystem, an inclusive environment with many startup events, and high-quality technical talent.

Thus, the methodology proposed by Cukier and Kon (2018) serves as the framework for our empirical analysis in this study and here we will adopt the term ‘emerging’ to refer to the evolving category according to their aforementioned classification criteria.

Seed accelerators

SAs play a central role in the development and growth of startup ecosystems. These agents act as catalysts and promoters of innovative entrepreneurship, first by encouraging the creation of new startups, and second by enhancing their chances of survival, growth, and scaleup. One of the most widely accepted definitions of SAs is that of Cohen and Hochberg (2014, p.4), who defined an SA as “a fixed-term, cohort-based programme, including mentorship and with an educational component, that culminates in a public pitch event named demo-day”. However, SAs are also “business entities that make seed-stage investments in promising companies in exchange for equity” (Dempwolf et al., 2014, p.26). SAs are mostly private, for-profit organisations with a clear business model (Tasic et al., 2015). Hathaway (2016) described the SA experience as a process of comprehensive, learning-by-doing education over a short period to accelerate the life cycle of young and innovative firms. SAs are mostly privately funded or backed by governments, corporations, or universities (Hallen et al., 2020).

However, SAs are not uniform agents. Instead, their methodology, organisation structure, and the profile of their tenant firms will vary significantly depending on the priorities, orientation, and maturity level of the EEs in which they are located. This variation leads to different criteria for evaluating the effectiveness and value added by SAs and creates difficulties in establishing key success factors (Albort-Morant & Ribeiro-Soriano, 2016) or a unified conceptual framework for SA research (Mian et al., 2016). The result is the lack of a widely accepted set of performance indicators, exacerbated by the unavailability of extensive quantitative empirical studies. The limited evidence gathered so far comes from qualitative-based studies with inconclusive results. While some studies have revealed that SAs have a positive impact (Cohen et al., 2019; Fehder & Hochberg, 2019; Hallen et al., 2020; Van Rijnsoever & Eveleens, 2021), others have suggested a neutral or even negative effect on accelerated startups (Gonzalez-Uribe & Leatherbee, 2017; Smith & Hannigan, 2015).

The most recent studies tend to question the benefits of SAs on hosted firms. For example, after comparing startups affiliated with 13 SA programmes with non-accelerated startups backed by venture capitalists (VCs), Yu (2020) concluded that accelerated startups were significantly more likely to close than non-accelerated firms. Similarly, Lukeš et al. (2019) also reported a negative effect of incubator tenancy on sales revenues and a negligible negative effect on job creation, based on a sample of innovative Italian startups. These results are surprising, given the strong support and substantial resources that most SAs receive from both private and public organisations. In summary, the empirical findings from the existing SA literature are limited and inconclusive. Undoubtedly, there are still several gaps in this topic that require further research with larger and more representative samples to more accurately and reliably assess the effect of SAs on hosted companies. This current study addresses this gap by providing new evidence for the impact of SAs on the performance of startups based on quantitative analysis and using a large data set of both accelerated and non-accelerated firms.

The impact of seed accelerators on investment and in growth of startups

A key indicator of the prospects and expectations of most high-tech companies, especially startups, is the level of funding raised from external investors, primarily VCs. New ventures that can attract external investment are believed to be more likely to survive and grow. In addition, attracting investment gives easier access to other external resources and capabilities (Colombo et al., 2006), hence making it simpler to fulfil the high-growth targets (Bowen & Declerk, 2008) of most new ventures. Although SAs are expected to nurture their hosted startups by providing some of the capabilities that make them more appealing to VCs and business angels, the findings reported in the literature fail to confirm the presence of a strong direct link between participation in SA programmes and the receipt of additional external funding. Indeed, studies of business incubators and SAs suggest that accelerated startups have better chances of attracting VC investment and closing investment rounds if they are run by founders with the right managerial, educational, and professional experience (Bertoni et al., 2011; Colombo & Grilli, 2010; Puri & Zarutskie, 2008). In theory, these areas are strengthened while startups are in SA programmes but they may not necessarily resolve any possible questions over the marketability of these projects.

Interestingly, firms with VC investment tend to excel over others in terms of most performance indicators (Dennis, 2004; Gompers & Lerner, 2001). In the context of startups, closing successive investment rounds implies extra marketplace credibility for companies and greater attractiveness for new investors. In addition, startups that secure funding in successive rounds of investment find it easier to access valuable skills and resources (Colombo et al., 2006; Hsu, 2006) and grow their team (Bertoni et al., 2011). Therefore, the academic literature seems to support the idea that receiving external funding positively impacts job generation. However, the role of SAs in making their tenant firms more attractive to investors has yet to be proven.

The interest of most startup founders in participating in acceleration programmes seems to be motivated by their higher chances of raising funding during or just after their tenancy in the SA. However, entrepreneurs with incubation experience might value the financial resources offered by incubators less than other startup entrepreneurs (Van Rijnsoever & Eveleens, 2021). In addition, VCs and business angels are free agents that are open to projects from any entrepreneur, regardless of whether the project is linked to an acceleration programme. Moreover, in emerging or evolving EEs, there are fewer investors and less funds available. Thus, SAs located in emerging EEs seem to mobilise business angels and small VC funds but encounter difficulties when trying to attract large investors willing to close series A or B rounds of investment (Cukier & Kon, 2018). According to Lukeš et al. (2019), accelerators appeal more to startups struggling to attract investment prior to revenue generation and searching for business advice, contacts, and skills development. Indeed, this factor probably applies even more to startups located in less developed EEs.

Consequently, being hosted in a SA located in an emerging EE might not be viewed as a sufficient guarantee to attract external investors to close deals above €100,000, and much less so for those in excess of €1 million. In conclusion, incubators and SAs in emerging EEs remain better positioned to attract small investors

as tenants but their advantage seems to disappear when the requested investment amounts are higher. In summary, despite the mixed results reported in the literature about the impact of SAs on the performance of their tenant firms, most studies claim that business incubation has at least a partial or indirect positive effect on performance in terms of sales, revenues, and job creation. Our hypotheses will align with these ideas, bolstered by our belief that incubated startups in emerging EEs possess more advantages than drawbacks when compared to their counterparts.

Technological level

The technological capacity to develop and launch cutting-edge products and services is expected to improve the prospects of startups (Zhang et al., 2019). But to what extent is that capacity a key factor in attracting investment, enhancing the chances of growth and the generation of more employment than other startups? The answer to that question remains largely unclear. To date, the relationship between EE maturity level and the technological level of startups has been poorly addressed in the academic literature. The literature review conducted by Triono et al. (2021) highlighted technological capability as one of the most crucial factors affecting startup performance at the organisational level.

In this current study, the technological level of the companies was measured with both objective and subjective measures. In line with previous work, we have used various objective indicators to classify startups according to their technological level: in-house R&D activities (Ahn et al., 2022; Kim, 1999), patents (Coombs & Bierly, 2006), and specifically, we have focussed on technological competitiveness (Kwon & Jung, 2012), measured as the development and release of cutting-edge products, services, and platforms. We have also incorporated subjective assessment, aligning with Kwon and Jung (2012), who emphasised that in the context of technology-based startup companies, subjective evaluation was more impactful compared to measuring objective technological capabilities.

Mature EEs are expected to host more technology-based new ventures than evolving ecosystems because they are better equipped with the resources needed to support the development of such ventures, including better access to capital, talent, networks, and market opportunities (Audretsch & Belitski, 2017). Thus, compared to mature EEs, emerging ecosystems are poorly endowed with the resources critical for the development and commercialisation of technology-based products and services. The maturity level of an EE is an important factor in determining the proportion of technologically advanced startups. Therefore, as an EE matures, the number of technologically advanced startups is likely to increase. Mature ecosystems also benefit from a higher concentration of experienced entrepreneurs, investors, and mentors who have knowledge and expertise in the development of technology. This expertise can be highly valuable to support the growth of technology-based startups, providing them with the skills, resources, and networks required to succeed.

Consequently, the proportion of new ventures able to develop technologically cutting-edge products and services is expected to be considerably higher in leading EEs such as Silicon Valley, New York, London, and Berlin when compared to smaller and less dynamic ecosystems. Indeed, high levels of research and development (R&D), creation of new knowledge, and the availability of scientific and technical personnel are features that distinguish technology-based and highly innovative firms from less technologically intensive firms. In this sense, the indicators presented in reports on EEs published by consultancy companies confirm that the top EEs have higher technological levels (Startup Genome, 2022). In summary, the few studies addressing the relationship between EE maturity level and technological level support the argument that the more mature the EE, the higher the proportion of high technology new ventures it will support.

Nonetheless, the tendency to consider every startup as a technology-based firm has resulted in the virtual absence of studies addressing differences in the performance, expectations, and prospects of startups as the result of different levels of technological intensity or orientation. The few studies that have examined this issue tend to point towards a greater likelihood of survival in technology-based firms than in non-technology-based firms (Del Sarto et al., 2020). This difference is partly because of the ability of technology-based firms to introduce radical innovation to the market (Löfsten, 2016). Hence, investments in R&D, which are particularly intensive in technology-based startup firms, are expected to positively affect performance of firms (Ehie & Olibe, 2010).

Previous work by Reichert and Zawislak (2014) analysed the relationship between technological capability and firm performance in terms of sales, profits, and markets, but not in terms of job creation. Supported by other authors (Camisón-Haba et al., 2019), the view adopted in this study is that being a startup is insufficient to define oneself as a technology-based or highly innovative firm. Consequently, the technological level of the new ventures, whether participating in acceleration programmes or not, is a factor worthy of analysis, especially in smaller EEs. In a context of poor evidence from the scientific literature, this current study set out to prove that the technological level of new ventures matters and is a key factor determining investment attractiveness and the capacity of firms to grow in terms of employees. More specifically, our hypotheses involving the technological components of companies anticipated improved performance indicators for startups that were more intensive in terms of R&D and that were capable of developing and applying cutting-edge technologies.

Business models

The term ‘business model innovation’ is defined as the capacity to introduce changes to the business of a firm to create, deliver, and capture more value for the firm and their customers (Bounchen & Fredrich, 2016). Most business models fall into one of just two categories: business-to-consumer (B2C) or business-to-business (B2B), each with different operation goals and modes. Startups with B2B models usually

develop technological advances and applications to solve problems or needs on the business side. To succeed in the B2B mode, entrepreneurs must build deep, long-term relationships with a relatively small number of companies. In general, as an EE matures, the number of startups that adopt the B2B business model tends to increase because mature ecosystems host a more established and diverse set of industries and sectors, as well as a larger pool of experienced entrepreneurs and investors interested in B2B ventures and with the knowledge and resources to support their growth. Furthermore, B2B startups typically require more specialised knowledge, resources, and connections to establish and grow, which may be more readily available in a mature EE.

Studies of performance differences resulting from the business model type are virtually non-existent. Consequently, there is scant empirical evidence of any disparities between B2B and B2C businesses in terms of performance, expectations, and prospects. One of the few studies that has explored the relationship between business model and investment raised was by Asipi and Durakovic (2020) and focused on companies from Serbia and Northern Macedonia, countries that are lagging in terms of entrepreneurial activity. Their findings were inconclusive, with indications that B2B sectors in Northern Macedonia tended to invest more compared to the B2C sectors while conversely, in Serbia, more was invested in B2C companies than their B2B counterparts.

The preference of VCs to fund B2B startups over B2C startups has also recently increased, likely because B2B startups are more capital-efficient, scalable in markets, likely to become profitable earlier, and have higher margins. In line with the growing wave of high-performing B2B startups in Europe, the recent study by Dörner et al. (2021) on the expectations and investment attractiveness of B2B startups shows that European B2B startups produce more output relative to their funding levels than those in the United States. Their work indicated that B2B market in Europe is not yet overrun by investors competing for the same deals, thereby making B2B firms more appealing to VCs. However, their technological complexity and need to convince other firms that they should become customers might still be perceived as an additional difficulty by SAs when comparing B2B with B2C ventures.

The scarce empirical evidence available in the literature regarding the relationship between business model and employment generation in startup companies tends to attribute a higher capacity for job creation to the application of B2B models (Durakovic & Cosic, 2019). Given all the above set out in the literature review, it seems that at least in advanced EEs, B2B startups tend to be more attractive to investors and have better chances of employment growth. In this current study we attempted to determine whether this situation holds true in emerging EEs.

Hypothesis formulation

Our literature review led us to formulate the following hypotheses.

Hypothesis 1: accelerated firms tend to outperform non-accelerated firms in terms of investment received, employment generated, and technological level.

The founders of new ventures are well informed about the different types of SAs and profiles of firms that each type of SA seeks. Therefore, they decide which type of SA they would prefer to enrol into accordingly.

Hypothesis 2 was related to the type of SAs preferred by firms in the scaleup phase and is divided into three sub hypotheses. Hypothesis 2.1: firms with higher levels of investment and job creation tend to enrol in SAs that prioritise scaleup and high-tech firms. Hypothesis 2.2: firms hosted by SAs that prioritise new ventures at an early stage of development, regardless their technological level, tend to be smaller, prefer B2C models, and receive less funding. Hypothesis 2.3: Apart from having a higher technological level, firms in SAs that prioritise technology-driven firms at an early stage of development, are expected to follow B2B models.

Next, hypothesis 3 referred to the size of the companies in SAs, in terms of their number of employees. Hypothesis 3: we expect new ventures with more employees to be older, receive more funding, be technologically advanced, and follow mostly B2B models. Our fourth hypothesis regarded the profiles of firms receiving higher levels of funding. Hypothesis 4: we expect firms that receive more funding to have more employees, a medium-to-high technological level, operate under a B2B model, and be older. Finally, we finish with hypothesis 5: firms with a medium-to-high technological level are expected to generate more employment, receive more funding, and mostly follow B2B models.

Model of analysis

Data

We conducted an empirical study in the emerging EE of Valencia, Spain. The main sources used to build the data set for this study came from the startup observatory of the Valencian startup association, the Sofia database by Conexo Ventures, the four main SAs operating in Valencia, and the websites of all the sampled firms. The final data set comprised 735 companies located in the Spanish region of Valencia and represented around 70% of the overall Valencian startup and scaleup ecosystem. With all the data collected at the end of 2020, the data set offered an accurate snapshot of the Valencian startup ecosystem in 2020.

Variables

All the variables used in this study were drawn from our academic literature review and are listed and explained below; they all refer to startup firms, regardless of whether they were linked to SAs.

Technological level

All the firms in the data set were classified according to three technological levels: user, adapter, and developer. Users are companies that simply make use of

technologies that are already available in the market to develop their products and services. Adapters are able to adapt, modify, and improve existing technologies and introduce these improvements into their products and platforms. Finally, developers are highly innovative ventures, operating in deep tech industries. They are strongly R&D-based and have a proven capacity to develop major, even disruptive, technological innovations. To meet the requirements of the statistical analysis methods applied in this study, we transformed this attribute into a dichotomous variable, with two options: *Conventional tech firms*: companies that are merely users of technologies already available on the market and *High-tech firms*: adapters and developers of advanced technologies.

Business model

Companies were classified as B2B or B2C as the two basic business models; firms initially classified as ‘other’ were reclassified accordingly.

Acceleration programme

This variable distinguished between accelerated and non-accelerated firms.

Accelerator type

Based on the data set, around 70% of the firms were created and developed with no initial relationship with acceleration programmes. These firms were classified as Level 1 for this variable. The remaining three levels referred to the 30% of firms that were or had been tenants of one of the three types of accelerators. Level 2: type A accelerators: startups hosted by Lanzadera Traction and Demium, whose acceleration programmes prioritised new ventures with a B2C orientation and mostly leveraging conventional tech, at an early stage of development. Level 3: type B accelerators, new ventures hosted by Lanzadera Growth, which specialises in hosting firms following B2C models with a mostly conventional level of tech. Unlike type A firms, companies in this group were already in a growth or scale up stage. Level 4: type C accelerators, including new ventures linked to Go Hub, the only accelerator in the Valencian ecosystem that openly prioritises early-stage firms with a deep tech orientation and following a B2B model.

Employees

This variable captured the size of the firms in the data set and was initially divided into four levels: 0 to 4 employees, 5 to 10 employees, 10 to 25 employees, and more than 25 employees. This variable was then transformed into dichotomous values: up to and including 10 employees, and more than 10 employees.

Funding received

This key variable captured the amount of external funding received by the firms in the data set. Only investments registered in official sources such as Crunchbase were included. The firms were split into four levels: no investment, less than €100,000, between €100,000 and €1 million, and more than €1 million. When converted into a dichotomous variable, they were considered as *Low investment*: under €100,000 or *Medium or high investment*: over €100,000.

Age: Foundation

This variable captured the age of the firms in the data set, with two options: up to 4 years old or 5 or more years old.

Table 1 shows the descriptive statistics for these variables.

Model and hypothesis testing

The previously stated hypotheses were presented in an overarching model of analysis that connects them with all the variables under study (Fig. 1).

To test the proposed hypotheses, six binary logistic regression models were created using SPSS 26 software. Several indicators were calculated to assess the goodness of fit of each model. First, the R² indicator was obtained. In logistic regressions, this indicator takes values that are much lower than in linear regression, with values of around 0.2 being considered acceptable. Second, a *p*-value of more than 0.05 in the Hosmer–Lemeshow test was recommended to ensure the fit of the model at a 5% significance level. Third, the correct classification table determined the percentage of the predicted outcomes that were correctly classified. The higher the percentage of correct predictions, the higher the fit of the model.

Results

The results of the estimated logistic regression models which allowed us to test the six hypotheses proposed in this study are presented in Table 2. The goodness of fit for the six models was sufficient, with R² values between 0.14 and 0.29. The percentage of correct classification ranged between an acceptable level of 67.5% and a high level of 86.4%, with these levels being considered adequate. The results of the Hosmer–Lemeshow test also indicated a satisfactory goodness of fit for most of the models.

The results for model 1 led to partial confirmation of hypothesis 1 (H1), which posited a link between performance and the acceleration process. The model showed that accelerated firms only outperformed non-accelerated firms in terms of investment received. Contrary to the H1 predictions, firms not backed by SAs were more likely to have a higher technological level. There were no conclusive results regarding the size of the firms.

Table 1 Descriptive data

Variable	<i>N</i> (%)
Age:	
- Up to 4 years	300 (40.8)
- 5 or more years	435 (59.2)
Size: Number of employees	
- 0–4	304 (41.3)
- 5–10	244 (33.2)
- 11–25	121 (16.4)
- > 25	67 (9.1)
Size (dichotomous)	
- 0–10	548 (74.5)
- > 10	188 (25.5)
Investment: funding received	
- No external investment	513 (69.7)
- < €100,000	108 (14.7)
- €100,000–€1 million	68 (9.2)
- > €1 million	47 (6.4)
Investment (dichotomous)	
- No or low investment ($\leq$ €100,000)	620 (84.4)
- Medium or high investment ($>$ €100,000)	115 (15.6)
Technological level	
- User	379 (51.6)
- Adapter	286 (38.9)
- Developer	70 (9.5)
Technological level (dichotomous)	
- Conventional tech	379 (51.6)
- Medium/high-tech	356 (48.4)
Business model	
- B2B	326 (44.4)
- B2C	237 (32.2)
- Other	172 (23.4)
Accelerator type	
- Non-accelerated	509 (69.3)
- Type A	165 (22.4)
- Type B	34 (4.6)
- Type C	27 (3.7)
Accelerator type (dichotomous)	
- Non-accelerated	509 (69.3)
- Accelerated	226 (30.7)

Source: Compiled by the authors

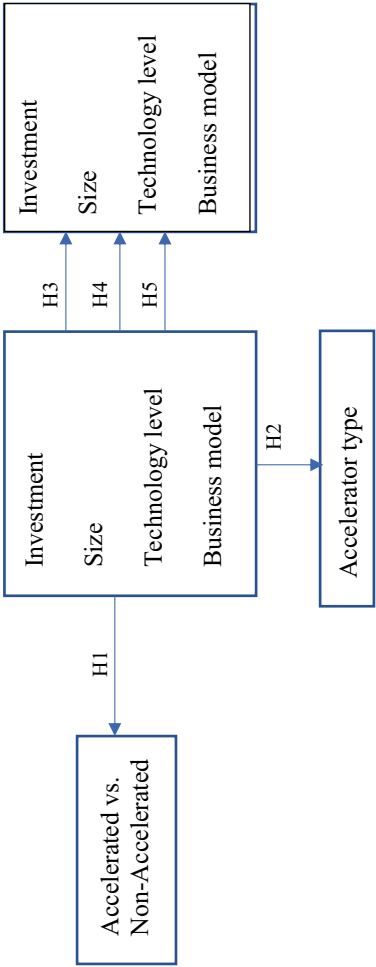


Fig. 1 Model and Hypotheses

Table 2 Results

Variables	Model 1: Accelerated vs non-accelerated		Model 2: Employees		Model 3: Funding		Model 4: Technology level		Model 5: B2C model		Model 6: B2B model	
	Coeff.	sig.	Coeff.	sig.	Coeff.	sig.	Coeff.	sig.	Coeff.	sig.	Coeff.	sig.
Constant	-1.915	0.000	-2.196	0.000	-3.950	0.000	-1.036	0.000	0.723	0.019	-2.276	0.000
Foundation	0.701	0.000	-0.885	0.000	-1.108	0.000	0.242	0.166	0.700	0.000	0.010	0.952
Tech. level	-0.315	0.027	0.050	0.746	0.909	0.000			-1.147	0.000	1.071	0.000
Employees	0.022	0.816			0.760	0.000	0.001	0.987	-0.262	0.009	0.345	0.000
Funding	0.733	0.000	0.590	0.000			0.389	0.000	0.235	0.038	-0.251	0.014
B2B	0.175	0.340	0.836	0.001	-0.235	0.437	1.129	0.000				
B2C			0.190	0.492	0.282	0.402	-0.554	0.013				
Accelerator A			-0.554	0.029			-0.389	0.054	0.440	0.032	-0.007	0.974
Accelerator B			0.843	0.031	0.504	0.274	-0.097	0.800	-0.193	0.654	0.125	0.742
Accelerators C			0.297	0.511	0.222	0.670	2.666	0.010	-1.837	0.079	1.719	0.007
No Accelerator					-1.009	0.000						
Test statistics:												
R2 Nagelkerke	0.138		0.194		0.286		0.228		0.204		0.198	
Hosmer-Lemeshow	21.422	0.006	18.661	0.017	8.877	0.353	8.611	0.376	6.622	0.578	10.035	0.263
Correct classification (%)	71.3		77.7		86.4		69.1		70.1		67.5	

Source: Own compilation

Source: Compiled by the authors

H2.1 predicted that firms with higher levels of investment and more employees preferred type B and type C SAs. These two types of SAs mainly hosted companies in more advanced stages of development that were more technology oriented. This hypothesis was not supported by models 2 and 3. Regarding size, only the propensity of type B SAs to host larger firms was confirmed. In terms of funding, we observed no investor preferences for either type B or C SAs. H2.2 referred to the SA type and company size. Our results linked smaller firms with type A SAs and bigger firms with type B SAs, while the relationship with type C SAs was unclear. No connection was observed between higher investment and any specific type of SA. Consequently, the predictions regarding funding were thereby refuted. Finally, the results from model 5 confirmed the preference of type A SAs for B2C models. Regarding H2.3, we confirmed the expected preference of type C SA to host new ventures with higher technological levels and B2B models. Type C SA is clearly oriented towards B2B models and is adverse towards startups following a B2C model.

H3 predicted that bigger startups (with more than 10 employees) would outperform smaller ones in all key indicators. This hypothesis was mainly tested with model 2 and was largely confirmed because a strong direct relationship between size and funding was observed, with larger firms tending to be older and more likely to follow B2B models. Only one result contradicted H3: firms with more employees were not necessarily more technologically advanced than the smaller companies.

H4 linked the profile of startups with the funding they received. In line with H3, model 3 confirmed the propensity of investors to fund older companies with more employees. A noteworthy result was the strong direct relationship between funding and technological level. Finally, and contrary to our expectations, no connection between investment and business model type was observed.

Lastly, moving on to H5, the expected relationship between technological level and employment was not confirmed. This was the only noteworthy result that contradicted H5; the other results predicted by H5 were confirmed. First, the direct relationship between funding and higher technological level, and second, firms with B2B models tended to fall into the high-tech group, whereas most firms with B2C models pertained to the conventional technology group.

Discussion

The results of this study help improve our understanding of the effects of incubation on innovative startups. To date, research on this topic has been insufficient (Dvoutely et al., 2018; Mian et al., 2016). A notable finding of this work was that companies in acceleration programmes were more likely to be younger, have more employees, and receive more funding than non-accelerated firms. This finding aligned with reports in the academic literature regarding the impact of SAs (Cohen et al., 2019; Fehder & Hochberg, 2019; Hallen et al., 2020; Van Rijnsoever & Eveleens, 2021). Conversely and unexpectedly, their technological level was lower than that of non-accelerated firms. Our findings suggest that, in the early stages, seed investors tend to place more trust in new ventures enrolled in an SA. This result

also aligns with the findings by Lukeš et al. (2019), who suggested that accelerators play an active role in attracting early-stage capital to their tenant firms.

In addition, firms in acceleration programmes created employment opportunities in a shorter period than non-accelerated firms. However, job creation did not always lead to better performance and prospects, especially if investment was primarily spent on recruiting new employees for marketing tasks rather than for R&D to develop more advanced prototypes. Firms that spent on these areas missed the opportunity to upgrade their technological level and capacity for innovation, perhaps reducing their chances of success in highly competitive markets. Similar to other studies about SAs (Lukeš et al., 2019; Yu, 2020), our work did not reveal a higher survival rate among firms in SAs. Rather, our results showed that SAs preferred to host recently founded firms and projects that were still in their early stages of development. These findings confirm that SAs in the Valencian startup EE effectively behaved as funding facilitators for tenant firms. External investors in this EE seemed to rely more on SA-hosted firms and viewed them as having better prospects.

Of particular interest was the finding that the largest companies (i.e. with more than 10 employees) tended to be older, received more funding, and mainly followed B2B models. This relationship was probably the most noteworthy finding because it revealed that new ventures with B2B models had a higher capacity to grow and generate employment. The tendency for B2B startups to become larger coincided with the study by Durakovic and Cosic (2019). In addition, the orientation of the SA also mattered, but only to a certain extent. The scope of the differences between different SA types was less than expected in terms of their size or the funding raised. Comparison between the SAs showed that firms with more employees were more likely to join SAs with programmes more oriented towards hosting firms already in the growth or scaleup stage, rather than in the early stage.

Our results also revealed that the number of employees in startups was carefully analysed by external investors. Companies able to maintain at least 10 employees were more credible and appealing to investors. Another major, and surprising finding was the lack of connection between company size and their technological level. This result cannot be directly compared with the existing literature, because previous studies have generally suggested that startups with more technology usually perform better, although previous work has primarily focused on financial and market aspects rather than employment generation (Ehie & Olibe, 2010; Reichert & Zawislak, 2014). Our finding implies that there were technological leaders with fewer than 10, and sometimes with even five employees, able to make major technological advances in the Valencian EE. Consequently, the technological level seemed to be a critical factor for attracting investors but not to grow in terms of employees. This behaviour is probably different in more mature EEs where technology leaders not only attract more investment but also manage to grow faster in terms of employees. In emerging EEs like that of Valencia, and in contrast to mature EEs, the number of employees is not a key variable to distinguish young, high-tech, innovative ventures from other startups.

Our model 3 addressed a key objective of this study, namely, identification of the factors behind the funding received by startups. This model had the best fit, with an R^2 value of 0.29 and 86.4% correct classification and gave rise to several notable

findings. First, older companies were more likely to receive external funding. Second, and more meaningfully, the technological level and funding of companies was directly correlated. This outcome reveals that investors preferred funding new ventures with a higher technological level and confirms the theory set out by Saemundsson et al. (2022), positing that R&D intensity and orientation are factors that induce investment.

The direct relationship connecting funding and firm size deserves further discussion. According to our model 2, the capacity to generate employment (at least 10 employees) was viewed by investors as an indicator of growth and of attractive prospects. However, caution should be applied when considering this result, especially when the increase in employees is not accompanied by a capacity to generate revenues. Indeed, the profile of the recruited employees is also usually scrutinised by the investors. While hiring mainly for R&D tasks is broadly accepted, investors tend to mistrust the large-scale recruitment of employees in marketing because this can be perceived as a desperate attempt to sell a non-competitive product. In such cases, investors will ignore employment growth. The negative relationship between funding and non-accelerated firms means that investors tended to penalise firms not engaged in any acceleration programme by investing less in them.

Another noteworthy finding was the strong direct relationship between B2B and technological level. This link probably stems from a higher R&D intensity in these companies. Firms with a B2C model tend to be younger, probably because of the shorter time most of these firms require to develop their products or services, and they mostly belong to the conventional tech group. In addition, and in line with Durakovic and Cosic (2019), new ventures under B2C models are smaller, with an overwhelming proportion of firms having fewer than 10 employees.

Contrary to the tendency in most top entrepreneurial hubs and reports in previous studies (Dörner et al., 2021), in the Valencian startup ecosystem, firms with B2C models tended to receive more funding than B2B companies. Upon deeper analysis, the descriptive data in this study revealed that the advantage of B2C models in attracting investors was only true for small investments under €100,000, and tended to be weaker for larger investment amounts. The direct connection between size and B2B was another key finding. Apart from employing more people, compared to B2Cs, firms operating under a B2B model assigned a much higher proportion of their employees to technical and development tasks than to marketing tasks.

Some non-significant results typical of emerging EEs and no longer present in more advanced EEs, are also worth mentioning. First, investors in the Valencian startup ecosystem had no preference for firms that followed B2B models. Second, none of the three SA types seemed to have attracted more investors: we found no special advantage to any of them in terms of the funding received by their tenant firms. Finally, the finding that SAs failed to attract truly innovative technology-based firms was of considerable note. This finding may seem especially contradictory, somewhat counterintuitive, and surprising because we would naturally expect technological capabilities to be treated as a determining factor for enrolment into SA programmes.

Conclusions

This study contributes to the literature on EEs by identifying the factors that determine the appeal of startups to investors and their employment growth prospects. The findings concerning business model type and technological level are particularly valuable as these are two components that have received scant or no attention in the existing academic literature. Of note, some key features of our descriptive data are applicable to other medium-sized entrepreneurial hubs and revealed major disparities when compared to more developed ecosystems. The first was the small size of startups: only 25% of the firms registered in the Valencian EE had more than 10 employees, a proportion that was probably higher in more developed hubs. The second was the low level of investment: according to our dataset, 70% of startups had no external investment, which was far higher than in more developed hubs. The third was the role of SAs: in recent years, the presence and impact of SAs in the Valencian ecosystem has increased. However, although their market share is mounting, they host only around 30% of the total population of startups in the EE. Another disparity lied in the low proportion of highly innovative technology-based firms. In the Valencian ecosystem, half of the startups could be classified as low or conventional tech, and the percentage of firms developing technology was just 10%. Finally, unlike in mature hubs, the preference for B2B models in the Valencian ecosystem was unclear: in the last four years, the proportion of companies founded in Valencia and following B2C models had increased rather than decreased.

Theoretical implications

Several theoretical implications can be derived from our findings. Firstly, researchers should reconsider the assumption that high technology startups tend to be larger. Indeed, our findings suggested that the growth of these firms probably depended more on their ability to implement effective strategies in funding and market areas rather than on excelling in the development of advanced technology. Our study highlights the significance of technological development in the market. Despite high-tech startups not necessarily being larger in size, they still exhibited the ability to secure more funding. This highlights the considerable market value and potential for future growth that is inherent in technologically superior startups.

Secondly, the efficacy of incubation programmes deserves further evaluation. Our findings raise questions about the ability of incubators, particularly in emerging EEs, to attract startups with good prospects and to set them on the path to success. Finally, our findings reveal that the profile of the most promising startups within the context of emerging EEs differs from that of those in more advanced ecosystems. This outcome emphasises the significance of the maturity level of the EE and suggests that a territorial-based approach should be adopted to properly consider the unique conditions of the local environment in terms of entrepreneurial orientation, talent retention, institutional support, or VC availability.

Practical implications

Several useful implications for managers can be derived from the findings. First, managers and founders of startups must analyse the different approaches followed by SAs and be aware of their orientation and preferences before approaching them. Second, accelerated firms tend to have a greater chance of receiving funding, but only for small investments. Of the 735 firms in our data set, only 47 have had received an investment of more than €1 million. We might expect the vast majority of these firms to be linked to an SA, but at 38.3%—only slightly above the 30% of accelerated firms in the whole data set—the actual figures refute that expectation and agree with the conclusions of Lukeš et al. (2019). In contrast, 70% of firms had received less than €100,000, thereby suggesting that accelerated firms had no advantage over non-accelerated companies in terms of closing big investment rounds. SAs in the Valencian ecosystem were effective at attracting small investors but found it hard to persuade VCs to participate in series A and B funding.

Our findings also provide a profile of startups with high prospects of attracting investment and scaling up. Such startups had at least 10 employees, followed a B2B model, and had a high technological level (i.e., they were a technology developer). Another valuable implication was that in Valencia, and probably also in other emerging EEs, technology leadership could be achieved with very few employees, as long as the new venture relied on external resources and subcontracting to access the resources required to develop technologically advanced products and services. Thus, in this sense, a smart partnership and technology transfer strategy can counteract the shortage of internal resources and assets.

Regarding business models, our findings suggest that firms with B2C models found it easier to obtain funding. However, this finding was true only for investments under €100,000, where 52% of B2C firms achieved such investment versus just 20% of firms with B2B models. However, the opposite was true for investments over €100,000. In total, 52% of such investments were provided to firms with a B2B model, versus just 26% for firms with a B2C model. Therefore, the finding that B2C firms received more funding was only true for small amounts and did not hold in general. In terms of policy implications, our findings suggest that government policies should favour incubators that prioritise new ventures with a high technological capacity and those that follow B2B models. These startups have the ideal profile to contribute to the local economy by mobilising resources and creating employment.

Study limitations

The limitations of this study include the fact that we did not analyse any variables linked to founders or managers. The skills and experience of the founding teams and staff of companies are critical for the prospects of any firm, especially startups. Thus, future research should gather and analyse data on the composition and behaviour of the managerial teams of startups. Another limitation was the funding data. The proportion of firms with external funding was probably much higher than it appears to be in the data set we used. The reason for this discrepancy was that many

firms receive funding but prefer to keep it confidential and so do not communicate it to major databases such as Crunchbase and AngelList. Consequently, the proportion of firms with external funding considered in this study was probably underrepresented. Thus, extra effort to check the actual funding levels of startups from different sources would be desirable in future work. Finally, regarding avenues for further research, we intend to add more variables to our analysis and to expand the size of our company samples in EEs with different maturity levels.

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