



# The entrepreneur and the ecosystem: extending and operationalizing EE theory from an embeddedness perspective

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## Abstract

Why do entrepreneurs leave their current entrepreneurial ecosystems to relocate elsewhere? While entrepreneurial ecosystem (EE) theory tends to assume that entrepreneurs remain embedded within their ecosystems, this study challenges that notion by examining ecosystem “leakage” and highlighting the permeability of EE boundaries. Drawing from an embeddedness perspective, we extend EE theory by developing hypotheses on relational, structural, family, and societal embeddedness. In doing so, we integrate both traditional and non-business-related inputs that influence entrepreneurial relocation decisions. Particularly, we provide a novel operationalization of EE inputs, also including those related to private well-being systems (e.g., cost of living, family support) and societal development (e.g., public safety, technological advancement). Using survey data from 522 entrepreneurs and applying adaptive LASSO and random forests, we find that non-business inputs significantly shape relocation decisions. Entrepreneurs weigh multiple dimensions of embeddedness when considering relocation. As well as business-related inputs contribute to retention, the presence of private well-being systems and advanced societal development significantly reduces the likelihood of leaving. When these non-business factors deteriorate, even ecosystems rich in traditional EE inputs may experience leakage. Overall, our findings suggest that ecosystem retention strategies must extend beyond economic incentives to address the broader social and institutional factors that sustain entrepreneurial embeddedness.

**Keywords** Entrepreneurial ecosystems · Entrepreneurial relocation · Ecosystem leakage · Relational embeddedness · Institutional embeddedness · Adaptive LASSO · Random forests

**JEL Classification** L26 · O18 · R11

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## 1 Introduction

Entrepreneurial ecosystem (EE) theory has become a widespread framework for understanding the conditions that support entrepreneurial activity within specific regions. Defined as a set of interdependent actors and factors that enable productive entrepreneurship within a territory (Stam, 2015; Wurth et al., 2023), EE theory centers on “the relationality between peoples’ actions and their cultural, societal, economic and political situational context” (Harrison, 2023, p. 1). The framework has gained traction among policymakers and scholars alike, with substantial interest from global institutions such as the OECD, World Bank, and European Commission (Ács et al., 2017; Mago & van der Merwe, 2023). At its core, EE theory posits that entrepreneurs operate within a structured environment where inputs—such as access to finance, talent pools, knowledge networks, and supportive policies—facilitate business creation and growth (Leendertse et al., 2022; Spigel, 2017; Stam & Van de Ven, 2021).

While EE theory has proven a powerful lens in examining the dynamics that drive the formation, growth, and success of the entrepreneurial activity (e.g., Gifford et al., 2021; Mack & Mayer, 2016; Spigel, 2017), it also comes with a number of partially unaddressed issues (e.g., Alvedalen & Boschma, 2017; Coad & Srhoj, 2023; Harrison, 2023; Stam & van de Ven, 2021). First, the embeddedness of entrepreneurs in their ecosystems is often assumed to be stable, meaning that ambitious entrepreneurs are expected to benefit from and contribute to their current regions over time (Stam, 2015). However, this assumption reinforces the idea that entrepreneurs will remain loyal to their region (Michelacci & Silva, 2007), while overlooking the fact that EE boundaries may have significant leaks, as entrepreneurs may choose to move from their current EE to a prospective EE when key inputs become insufficient or misaligned with their needs (Spigel & Harrison, 2018). Consistently, while the literature has extensively studied entrepreneurial entry and success, less attention has been paid to why some entrepreneurs relocate from a current EE to a prospective one. In this perspective, EE theory insufficiently accounts for “leaks” in EEs—cases in which entrepreneurs leave their current EE due to “push factors” (as opposed to “pull factors” that attract them to a prospective EE), thereby disrupting the local accumulation of entrepreneurial resources.

Second, despite EE theory draws from the “socially embedded nature of entrepreneurship,” (Spigel & Harrison, 2018, p. 155), it examines the entrepreneurial embeddedness within the ecosystem as primarily determined by business-related resources and institutional frameworks. However, embeddedness is not conceptually confined to business interactions alone (Roundy, 2019a; Wigren-Kristoferson et al., 2022). And still, “one aspect of EEs often overlooked in the emerging literature is the fundamental role played by social and cultural factors in shaping entrepreneurship” (Brown, & Mason, 2017, p. 14). Indeed, “entrepreneurs, like all individuals, are embedded within broader socio-economic contexts that shape their ability and willingness to remain in a region” (Harrison, 2023, p. 3). Drawing on an embeddedness perspective (Granovetter, 1985), we argue that entrepreneurial decisions are shaped by various forms of embeddedness within an ecosystem, including *relational*, *structural*, *family*, and *societal embeddedness*. When these broader conditions deteriorate, the embeddedness of the entrepreneur with the region weakens, increasing the likelihood of leakage—the departure of entrepreneurs from a region, even in spite of the continued presence of strong business-related inputs. Consider a region where venture capi-

tal is abundant, incubators are active, and knowledge spillovers are strong, yet the cost of living is prohibitively high, housing is scarce, and public services are strained. For example, public safety has been cited as key driver of entrepreneurial migration in high-cost innovation hubs such as San Francisco and London, despite the presence of world-class business resources (Harmon, 2024; Zahn, 2023). In the Silicon Valley, the high cost of living, particularly housing expenses, has contributed to a “mass exodus” of individuals and businesses seeking more affordable locations (Quittner, 2016). Such cases collectively suggest that EE leaks are a failure of the ecosystem to sustain embeddedness across multiple dimensions. Yet, EE theory, as currently formulated, tends to overweight business-related inputs to the exclusion of broader socio-economic conditions that shape the embeddedness of an entrepreneur to their current EE.

Third, several scholars note the vagueness surrounding the EE theory (e.g., Brown et al., 2023; Harris & Menzel, 2023). Indeed, EE theory has been criticized for its conceptual elasticity, with some scholars arguing that it risks becoming “everything and nothing at the same time” due to the broad and often inconsistent application of its core constructs (Harrison, 2023; Leendertse et al., 2022). The lack of precision in defining what constitutes an EE has led to challenges in measuring inputs and identifying their relative importance, creating significant conceptual overlap among different input categories, leading to an under-operationalization of EE’s inputs.

Fourth, as Cao and Shi (2021) note, “existing research has separately explored specific aspects” (p. 76), rather than examining how the various inputs interact to shape entrepreneurial intentions. Similarly, Cavallo et al. (2019) argue that “no holistic approach to entrepreneurship has focused on its interrelated aspects” (p. 1292), leaving critical gaps in our understanding of how ecosystems operate as a whole. This fragmented view limits the ability to fully grasp the decision-making processes that influence entrepreneurs, particularly those who are considering leaving EE (Roundy, 2019b).

To overcome these limitations, the present study extends EE theory by incorporating traditional and non-business-related inputs linked to the entrepreneurial embeddedness to the ecosystem. In particular, we focus on potential EE leaks by explicitly examining the push factors that drive entrepreneurs to leave their current EE in favor of a prospective EE. Moreover, we provide a novel operationalization of EE inputs, integrating both traditional and non-business inputs. In doing so, we assess the relative significance of these inputs in shaping entrepreneurial relocation decisions, offering deeper insight into how different embeddedness mechanisms contribute to an entrepreneur’s decision to leave their current EE.

To substantiate our lines of reasoning, we first undertook a multi-step process following the main phases of item generation, item allocation and refinement (Bagozzi & Yi, 1988; DeVillis, 1991). Then, to validate our scales associated with traditional and candidate EE inputs, we collected primary data from 522 entrepreneurs operating across diverse regional EEs through a survey including a series of perceptual items and demographic variables. Next, to test our theoretical arguments, we consistently relied on OLS regression with adaptive LASSO regularization (Zou, 2006) and random forests (Breiman, 2001).

Through the integrative assessment of the various facets of embeddedness, our findings address the critical gaps in EE literature regarding entrepreneurial relocation intentions. Overall, our findings provide empirical support for the proposed hypotheses. Indeed, the results show that the presence of private well-being systems and the stage of societal devel-

opment, in addition to traditional EE inputs and the active presence of successful companies, are key determinants in shaping entrepreneurial relocation intentions.

It is worth noting that a major critique of EE theory is its tendency toward over-specification, incorporating an ever-expanding list of factors that blur its conceptual boundaries (Harrison, 2023). This paper does not argue for the indiscriminate expansion of EE theory but rather for a structured refinement that maintains theoretical clarity. Specifically, key outcomes and mechanisms should be identified, and inputs must be theorized parsimoniously to ensure analytical precision. In the analysis of EE leaks, this study empirically substantiates that each of the embeddedness facets are significant determinants of current EE leave. Building on this study, future research can further investigate the relationship between the embeddedness and retention across individual entrepreneurs and region-specific characteristics. Additionally, while this study focuses on push factors driving entrepreneurs to leave their current EE, future research could inspect key mechanisms related to the pull factors that enhance the attractiveness of prospective EEs, offering a complementary perspective on entrepreneurial mobility decisions.

## 2 Theoretical background and hypotheses development

### 2.1 EE inputs and the decision to leave

EE theory identifies ten core inputs that shape entrepreneurial success (Stam, 2015). These inputs collectively support ecosystem functioning by facilitating resource access and fostering innovation (Gifford et al., 2021; Leendertse et al., 2022; Stam, 2018). Borrowing from relational embeddedness, which underscores the role of social networks in economic decision-making (Harima & Harima, 2024; Mawdsley & Somaya, 2021), we consistently advance that entrepreneurs are deeply integrated into trust-based relationships within their ecosystems, which grant access to critical resources such as knowledge, talent, and financial support (Granovetter, 1985; Jack & Anderson, 2002). These networks reduce search and transaction costs, facilitate collaboration, and provide stability (Uzzi, 1997). Relocating disrupts these embedded ties, requiring entrepreneurs to rebuild trust and reestablish networks in an unfamiliar EE—an often time-consuming and uncertain process. For instance, financiers rely on social capital and reputation to assess investments, and talent acquisition frequently occurs through referrals within trusted networks (Jack & Anderson, 2002). Severing these ties increases the costs and risks associated with relocation, making it less appealing despite potential pull factors in a prospective EE. From a broader perspective, disembedding from an EE introduces uncertainty and potential inefficiencies. Established ties provide predictability, reducing the risks associated with business decisions (Granovetter, 1985). Consequently, the stronger an entrepreneur's relational embeddedness within an EE, the lower the likelihood of relocation, as the costs of severing existing networks often outweigh the benefits of moving. As a result, we advance the following hypothesis:

**Hypothesis 1 (H1)** The EE theory's inputs, as traditionally conceptualized, are associated with a lower likelihood of relocating from the current EE to a prospective EE.

## 2.2 The active presence of successful companies

Stam (2015) has inspired extensive research on the determinants of entrepreneurial success within EEs, particularly regarding how different inputs influence entrepreneurial outcomes and decision-making processes. A prominent perspective in this literature highlights the role of successful companies—especially high-growth and large firms—in shaping EEs by enhancing access to strategic resources, fostering partnerships, and reinforcing network effects. High-growth firms and large companies often serve as central nodes within local business networks, facilitating the exchange of knowledge, capital, and business opportunities. Their presence creates a “gravitational pull,” attracting smaller ventures and embedding them in a dense web of strategic relationships, making relocation costly due to the risk of severing these connections. Coad et al. (2025) underscore that high-growth firms enhance EE vibrancy by fostering resource flows, stimulating innovation, and facilitating collaboration. Entrepreneurs operating in ecosystems with a strong presence of high-growth firms benefit from greater opportunities for market access, resource leverage, and knowledge spillovers. Herzog et al. (2024) emphasize the role of large companies as ecosystem anchors that provide stability, supply chain collaborations, and mentorship, further reinforcing the entrepreneurial environment. These findings reinforce the idea that successful firms, rather than broader regional development alone, play a decisive role in structuring entrepreneurial ecosystems and anchoring ventures within them.

From this perspective, the active presence of successful companies is a key factor influencing entrepreneurial relocation patterns. Structural embeddedness theory (Granovetter, 1985) suggests that entrepreneurs’ positions within network structures—particularly their ties to influential actors like high-growth and large firms—affect their strategic opportunities and constraints (Xu et al., 2023). Successful companies function as hubs that connect smaller ventures to broader markets and innovations, reinforcing entrepreneurs’ dependence on the ecosystem’s resources and relationships (Gulati, 1998). Agrawal et al. (2014) provide further insight into the role of firm size diversity in regional innovation. Their study shows that regions with both large R&D labs and numerous small firms experience a significant innovation premium, primarily due to spin-out formation and enhanced knowledge diffusion. This aligns with our argument that successful firms enhance EE dynamics not just by stabilizing networks but also by fostering innovation through firm interactions.

Given these insights, we propose that the presence of successful companies within an EE reduces the likelihood of entrepreneurial relocation. Entrepreneurs embedded in ecosystems with high-growth and large firms are less inclined to relocate due to the costs of rebuilding strategic relationships and accessing equivalent resources in a new environment (Uzzi, 1997). Thus, while Stam’s (2015) ten core EE inputs provide a foundational framework for understanding EE function, the active presence of successful companies introduces a distinct mechanism that is not fully captured by these traditional inputs. Therefore, we propose the following hypothesis:

**Hypothesis 2 (H2)** The active presence of successful companies (e.g., high-growth and large companies) in the region is associated with a lower likelihood of relocating from the current EE to a prospective EE.

## 2.3 The role of private well-being systems

The role of non-business-related inputs in entrepreneurial decision-making, especially from an embeddedness perspective, has been explored in various studies that highlight how personal, familial, and community connections shape entrepreneurs' decisions. Granovetter's (1985) embeddedness theory underscores the significance of social relationships and networks, not just in economic transactions but in broader decision-making contexts. Thus, as far as entrepreneurs are embedded in a network of social ties, including those related to personal well-being and family stability, their decisions extend beyond purely business considerations. Building on these premises, we propose that well-established private well-being systems, such as affordable cost of living, mental health services, and family facilities, are highly relevant in predicting the likelihood of entrepreneurs relocating to another region's EE.

*Family embeddedness* refers to the deep ties that entrepreneurs and their families establish within the local well-being systems of a region (Aldrich & Cliff, 2003; Cruz et al., 2012). These systems, encompassing healthcare, lifestyle, and cost-of-living advantages, create a sense of stability and satisfaction for both the entrepreneur and their family (Zukin & DiMaggio, 1990). In this context, the decision to relocate is also a personal and relational choice (Spigel, 2017). Entrepreneurs embedded in these systems rely on local services and support structures that facilitate both their business operations and their family's well-being. In this perspective, relocating would sever these personal and family ties. For instance, the cost of living in a region can significantly influence an entrepreneur's decision to stay, as affordable housing and daily expenses reduce financial pressure on both the entrepreneur and their family. Mental health and well-being services also contribute to a supportive environment that promotes a sustainable work-life balance, preventing burnout and fostering long-term entrepreneurial engagement. Similarly, family facilities, such as schools, recreational options, and family-friendly policies, play a pivotal role in ensuring that entrepreneurs feel embedded not just in the business community but in the local societal framework that supports their personal lives. When these private well-being systems are lacking or insufficient, the likelihood of entrepreneurs choosing to relocate their business to another ecosystem increases. Without affordable housing, access to quality healthcare, or family support services, entrepreneurs may find their personal and family needs unmet, prompting them to seek alternative regions that offer better living conditions.

In this way, private well-being systems are a key, non-business-related dimension of embeddedness that could be considered alongside traditional EE inputs. This dimension complements the traditional business-related inputs of EE theory, as well as the presence of successful companies, by addressing the private-life needs of entrepreneurs. While business resources such as networks, finance, and leadership are key for entrepreneurial success, the well-being of the entrepreneur and their family is equally relevant. Accordingly, we propose the following hypothesis:

**Hypothesis 3 (H3)** The private well-being systems (e.g., cost of living, mental health services) development in the region is associated with a lower likelihood of relocating from the current EE to a prospective EE.

## 2.4 The role of the societal stage of development

To complement the view, we argue that the stage of societal development also plays a significant role in predicting entrepreneurial willingness to leave their EE. Indeed, entrepreneurs are not only embedded in business networks but are also deeply connected to the broader societal infrastructure of the region in which they operate (Audretsch et al., 2019). When entrepreneurs perceive themselves to be part of a virtuous society—one characterized by public safety, technological advancement, accessibility and inclusivity—they are more likely to remain committed to their current ecosystem. We particularly anchor this argument in the concept of *societal embeddedness*, which emphasizes that entrepreneurs are tied not just to business inputs but also to the societal context of their region (Rohe et al., 2023). The more embedded entrepreneurs are in this societal infrastructure, the harder it becomes to justify a move to a new, less familiar region where these societal supports might not be as robust or reliable. Elements such as public safety and technological development contribute to the overall sense of stability and social cohesion, which may collectively contribute to reinforce a sense of attachment to the region (Redhead & Bika, 2022; Schiefer & Van der Noll, 2017).

Leaving a region with a high degree of societal development would mean potentially losing these supports. For example, public safety ensures a stable environment for conducting business without the fear of crime or instability, which can be a key concern in regions where safety is less assured. Similarly, the technological rate of advancement allows entrepreneurs to stay at the forefront of innovation, giving them access to new tools, markets, and operational efficiencies. Thus, we argue that societal development represents a non-business-related dimension of embeddedness that complements both private well-being systems and traditional EE inputs. The societal stage of development consistently offers entrepreneurs the broader social stability and technological resources needed to succeed, making relocation a less attractive option. As a result, we advance the following hypothesis:

**Hypothesis 4 (H4)** The level of societal development (e.g., public safety, technological advancement) of the region is associated with a lower likelihood of relocating from the current EE to a prospective EE.

## 3 Methodology

### 3.1 Data collection and sample characteristics

To test our research hypotheses, data were collected through a structured survey administered to entrepreneurs operating across diverse regional EE. The survey was designed based on a multi-phase process following the psychometric literature (Bagozzi & Yi, 1988; DeVillis, 1991). The data collection took place during the spring and early summer of 2024. Prior to the survey administration, a pre-testing phase was conducted, which involved pilot tests and informal interviews with a subset of participants. This phase helped identify ambiguous or misleading items, and the questionnaire was refined accordingly for clarity and to ensure all items accurately reflected the constructs under investigation. In this phase, feedback from experts was incorporated to ensure the comprehensiveness of the scale, particularly

concerning ecosystem inputs, the active presence of successful companies, private well-being systems, and societal development.

The final version of the questionnaire used in this study consisted of multiple items for each of the variables presented in Table 5, measured on a 7-point Likert scale. The survey was administered to a total of 543 entrepreneurs, after excluding respondents who either did not meet our inclusion criteria or provided incomplete answers. These criteria required participants to be active entrepreneurs with a high proficiency in English, ensuring comprehension of the survey items. Entrepreneurs represented a variety of regional contexts and industrial sectors, enhancing the generalizability of the findings. To further enhance data reliability, four attention checks were incorporated into the survey (Berinsky et al., 2016), and the order of items was randomized, with some reverse-coded to mitigate potential response biases (Groves et al., 2011). This led to a total of 522 valid responses. Participants were compensated for their time in recognition of their contribution. Table 1 summarizes the key characteristics of our sample.

### 3.2 Measures

The dependent variable in this study is the entrepreneur's willingness to leave the current EE. This variable is measured through the 7-point Likert scale question: "How likely are

**Table 1** Key characteristics of the sample ( $n = 522$ )

<i>Gender</i>		<i>Age</i>	
Male	264 (50.6%)	Mean	39.414
Female	258 (49.4%)	Std. dev	12.093
<i>Marital status</i>		Min	18.000
Single	324 (62.1%)	Max	71.000
Married	198 (37.9%)	<i>Number of children</i>	
<i>Education</i>		Mean	0.525
MBA	98 (18.8%)	Std. dev	0.834
Degree/PhD	277 (53.1%)	Min	0.000
Other	147 (28.1%)	Max	6.000
<i>Area of birth</i>		<i>Income level</i>	
United Kingdom	181 (34.7%)	1	26 (5.0%)
European countries	117 (22.4%)	2	107 (20.5%)
United States	130 (24.9%)	3	230 (44.1%)
Australia	29 (5.6%)	4	143 (27.4%)
Other	65 (12.4%)	5	16 (3.0%)
<i>Geographical location</i>		<i>Experience (years)</i>	
United Kingdom	209 (40.0%)	Mean	8.400
European countries	122 (23.4%)	Std. dev	7.628
United States	159 (30.5%)	Min	0.000
Australia	32 (6.1%)	Max	46.000
<i>Living area</i>		<i>Number of registered patents</i>	
Urban	371 (71.1%)	Mean	0.184
Rural	151 (28.9%)	Std. dev	0.626
<i>Industry type</i>		Min	0.000
Low tech	396 (75.9%)	Max	5.000
High tech	126 (24.1%)		

you to consider relocation to another region's entrepreneurial ecosystem, thereby leaving your current ecosystem, within the next three years?" This measure follows prior research in entrepreneurial ecosystems (Bischoff, 2021). The choice of a three-year time frame aligns with evidence from the literature on relocation and entrepreneurship, where such a period is commonly required for individuals and businesses to plan and execute significant transitions. For instance, Davidsson and Honig (2003) found that it typically takes two to three years for nascent entrepreneurs to transform initial intentions into established businesses. Similarly, studies on economic relocation suggest that relocating a firm involves not only physical movement but also the reestablishment of networks, compliance with new regulations, and setting up operational structures, all of which can extend over some years (Peltenbarg et al., 2002).

For operationalizing the independent variables pertaining to the inputs from the EE theory, as well as those related to the active presence of successful companies, private well-being systems, and societal development, we adopted a multi-step process from the psychometric literature (Bagozzi & Yi, 1988; DeVillis, 1991). Our approach followed three main phases: (1) item generation, (2) item allocation and refinement, and (3) scale validation. The first step involved generating initial pools of scale items based on extensive literature reviews underpinning entrepreneurship studies. This step also included informal consultations with industry experts and scholars familiar with the constructs to be measured. We iteratively conducted open-ended reviews of relevant literature and gathered qualitative insights through exploratory discussions with participants operating in various regional EE. These insights helped us develop potential items for each input category, such as networks, finance, talent, and leadership, among others. We utilized qualitative data coding techniques (Clark & Watson, 1995) to organize recurring themes, which were then translated into specific scale items. In parallel, feedback from experts in the field was integrated into the list to ensure comprehensiveness and clarity. During this phase, we also performed in-vivo coding to identify the most relevant themes for each ecosystem input. To enhance the reliability of the coding procedures, we also relied on K-Alpha calculator, and the Krippendorff's Alpha exhibited satisfactory levels of agreements among the coders (Marzi et al., 2024). The second phase involved refining the initial item pool to ensure relevance and eliminate redundancy. Through a series of focus groups and pre-tests, we collected feedback on item clarity and contextual appropriateness. During this stage, we carefully refined the wording of items and removed any that excessively overlapped with other constructs. A series of informal reviews by experts and scholars helped ensure that all items accurately captured the nuances of their respective categories.

We built the first version of the questionnaire with the refined items, ensuring that the scale was contextually adapted to regional entrepreneurial conditions while maintaining theoretical consistency. At this point, we included multiple items per variable to capture a broad spectrum of responses, utilizing a 7-point Likert scale to measure agreement. Subsequently, explanatory factor analysis was used to assess the underlying factor structure and select the items that best represent each construct. In doing so, we employed a varimax rotation and determined the optimal number of factors based on the Kaiser's criterion (eigenvalue greater than one) and on the proportion of explained variance with threshold 0.5 (Ford et al., 1986). Weak items (factor loading lower than 0.7) or items not loading on the intended construct were dropped, leading to a total of 49 items. From this analysis, 19 first order constructs emerged, which were clustered into four second order constructs:

- EE theory's related inputs (EE), comprising 10 first order constructs: networks (Net), leadership (Lead), finance (Fin), talent (Tal), knowledge (Know), support services (Supp), formal institutions (Form), culture (Cult), infrastructure (Infr), demand (Dem);
- Active presence of successful companies (SC), including two first order constructs: active presence of high-growth companies (High), active presence of large companies (Large);
- Private well-being systems (PW), consisting of four first order constructs: cost of living (Cost), leisure services (Leis), mental health services (Heal), family facilities (Fam);
- Societal development (SD), comprising three first order constructs: accessibility and inclusivity (Incl), public safety (Safe), technological advancement (Tech).

As a final validation, confirmatory factor analysis was performed (Kline, 2010, Chap. 9). All constructs demonstrated convergent validity (all factor loadings greater than 0.7 and average variance extracted greater than 0.5, as recommended by Fornell and Larcker, 1981), composite reliability (composite reliability index greater than 0.7, as recommended by Hair et al., 2009), and discriminant validity (average variance extracted greater than squared correlations with other constructs, as recommended by Fornell and Larcker, 1981, and heterotrait-monotrait ratio lower than 0.85, as recommended by Henseler et al., 2014). In the Appendix, Table 5 provides the full list of items together with summary statistics and factor loadings resulting from confirmatory factor analysis, and Table 6 reports validity indices for each construct. Measures indicating the key characteristics of the sample, detailed in Table 1, were utilized as control variables. These include demographic attributes (i.e., gender, age, marital status, and number of children), socioeconomic status (i.e., education, and income level), geographical factors (i.e., area of birth, and living area), and professional variables (i.e., experience, industry type, and number of registered patents).

### 3.3 Analytical techniques

We applied two distinct analytical techniques: linear regression with adaptive LASSO regularization (Zou, 2006), and random forests (Breiman, 2001). The choice of linear regression as primary analytic method is motivated by transparency. In fact, linear regression allows to assess the net impact of each independent variable on the dependent variable: each regression coefficient indicates the expected change of the dependent variable for a unit increase of an independent variable at constant value of the other ones. However, parameter estimation in linear regression with a large number of independent variables is problematic because ordinary least squares (OLS), although unbiased, may suffer of high variance, thus leading to inaccurate predictions. In order to overcome this issue, we use the adaptive LASSO regularization (Zou, 2006), which imposes a shrinkage towards zero to the estimated coefficients, with the result of a lower mean squared error and the elimination of independent variables with low predictive relevance. Our preference towards adaptive LASSO over other regularization methods relies on the oracle property, which guarantees a consistent selection of independent variables in large samples. For example, standard LASSO regularization (Tibshirani, 1996), which has been recently employed to predict high growth firms (Chae, 2024; Coad & Srhoj, 2020) and bankruptcy risk (Altman et al., 2023), may lead to an inconsistent selection (Zou, 2006). The adaptive LASSO regularization is defined as:

$$\widehat{\beta}_{AL} = \operatorname{argmin}_{\beta} (\operatorname{SSR}(\beta) + \lambda \|W\beta\|_1)$$

where  $\operatorname{SSR}(\beta)$  is the sum of squared residuals, which is minimized by OLS,  $W$  is a diagonal matrix including positive weights for the coefficients, and  $\lambda$  is a non-negative tuning parameter expressing the amount of regularization. For the oracle property to hold, each diagonal element of  $W$  must be set as  $w_j = |\beta_j^*|^{-\gamma}$ , where  $\beta_j^*$  is a root- $n$  consistent estimate of the  $j$ -th coefficient, and  $\gamma$  is a positive constant with suggested values 0.5, 1, or 2 (Zou, 2006). Such weights ensure that coefficients with smaller value have higher chance to be set to zero. Since the oracle is an asymptotic property, it is important to ensure that the sample is sufficiently large in order to interpret the selected items as meaningful predictors of the intention to leave the ecosystem. Using R for Statistical Computing (R Core Team, 2024), package ‘pwr’ (Champely, 2020), we computed that, with our sample size (522 observations) and number of independent variables (61, i.e., 49 items plus 12 control variables), the t-test can detect a Cohen’s  $f^2$  equal to 0.068 with power 0.8 at 5% significance level. Since  $f^2$  values of 0.02 and 0.15 are considered, respectively, small and medium effect sizes (Cohen, 1988), we can conclude that our sample size is large enough to allow a reasonably powerful detection of the items predicting relocation decisions.

Differently from linear regression, random forests follow a non-parametric approach to prediction. Initially proposed by Breiman (2001), random forests are tree-based models that are increasingly used in business and management research due to their capability to cope with high dimensional problems, non-linear relationships and complex interactions (Iyengar et al., 2022; Jin et al., 2024; Perboli & Arabnezhad, 2021; Yildirim et al., 2021). As such, feature importance measures based on random forests can provide a more accurate assessment of the predictive relevance of independent variables compared to linear regression. The state-of-art measure for feature importance in random forests is permutation importance, which consists in the assessment of the loss in predictive accuracy when the dependent variable is predicted based on random permutations of an independent variable. The more the predictive accuracy decreases, the higher is the importance of the variable. Here, we consider the permutation importance measure proposed by Strobl et al. (2007), which is robust when independent variables have a different scale of measurement or number of categories. However, the disadvantage of random forests relies on a weaker interpretability compared to linear regression. In fact, it is not possible to assess the effect of a change in an independent variable, like regression coefficients do, but only how much independent variables individually contribute to reduce the prediction error.

## 4 Results

### 4.1 Adaptive LASSO regression

The choice of weights is a critical step when using the adaptive LASSO regularization, because they must be based on a root- $n$  consistent estimate of parameters for the oracle property to hold. The natural candidate for this choice is the OLS estimator but, due to the potentially high variance in case of a large number of independent variables, it may have a distortive effect on the regularization. For this reason, we firstly computed the variance inflation factor for each item, and inspected the OLS estimates for the model including

all independent and control variables. Since all variance inflation factors were less than 5 (O’Brien, 2007) and no anomalous standard error emerged, we concluded that OLS estimates were adequate to construct the adaptive LASSO weights. Afterwards, tuning parameters  $\lambda$  and  $\gamma$  were selected based on 10-fold cross-validation. All these computations were performed using R for Statistical Computing (R Core Team, 2024), package ‘glmnet’ (Friedman et al., 2010).

The adaptive LASSO regularization selected a total of 11 items out of 49: four related to traditional EE inputs (*Lead\_1*, *Fin\_2*, *Know\_3*, and *Dem\_2*), two related to the active presence of successful firms (*High\_3* and *Large\_2*), three related to private wellbeing systems (*Cost\_2*, *Leis\_1*, and *Fam\_1*), and two related to societal development (*Incl\_2* and *Safe\_2*). Also, 7 out of 12 control variables were selected, precisely: age, marital status, education, income level, area of birth, living area, and experience. OLS estimates for the linear regression model including the selected variables are reported in Table 2, while Table 3 shows the analysis of variance (ANOVA) for first and second order constructs. ANOVA complements OLS estimates, which refer to single items, by assessing the predictive relevance of groups

**Table 2** OLS estimates for the linear regression model including the variables selected by the adaptive LASSO regularization

	Estimate	Std. error	p-value
(Intercept)	7.926	0.345	0.000***
Lead_1	-0.068	0.040	0.087.
Fin_2	-0.051	0.034	0.128
Know_3	-0.081	0.038	0.036*
Dem_2	-0.081	0.042	0.054.
High_3	-0.130	0.040	0.001***
Large_2	-0.082	0.040	0.041*
Cost_2	-0.051	0.029	0.080.
Leis_1	-0.070	0.042	0.098.
Fam_1	-0.070	0.037	0.056.
Incl_2	-0.088	0.041	0.032*
Safe_2	-0.063	0.032	0.047*
Age	-0.011	0.005	0.016*
Marital status: “married” vs “single”	0.312	0.104	0.003**
Education: “MBA” vs “other”	0.352	0.147	0.017*
Education: “degree/PhD” vs “other”	0.473	0.113	0.000***
Income level	-0.201	0.057	0.001***
Area of birth: “Africa” vs “Europe”	-0.099	0.196	0.614
Area of birth: “America” vs “Europe”	0.016	0.114	0.892
Area of birth: “Asia” vs “Europe”	0.046	0.255	0.858
Area of birth: “Australia” vs “Europe”	0.727	0.213	0.001***
Living area: “urban” vs “rural”	-0.362	0.110	0.001***
Experience (years): (1,5] vs [0,1]	-0.804	0.182	0.000***
Experience (years): (5,10] vs [0,1]	-0.501	0.207	0.016*
Experience (years): [10, +∞) vs [0,1]	-0.687	0.201	0.001***

Residual standard deviation: 1.053 on 497 degrees of freedom

R-squared: 0.454

“.” p-value<0.1; “\*” p-value<0.05; “\*\*” p-value<0.01; “\*\*\*” p-value<0.001

**Table 3** Analysis of variance (type II) for first and second order constructs

	SoS	DoF	F statistic	<i>p</i> -value
<i>EE</i>	14.886 (2.1%)	4	3.356	0.010*
Net	—	—	—	—
Lead	3.264 (0.5%)	1	2.943	0.087.
Fin	2.573 (0.4%)	1	2.321	0.128
Tal	—	—	—	—
Know	4.923 (0.7%)	1	4.440	0.036*
Supp	—	—	—	—
Form	—	—	—	—
Cult	—	—	—	—
Infr	—	—	—	—
Dem	4.126 (0.6%)	1	3.721	0.054.
<i>SC</i>	16.250 (2.3%)	2	7.328	0.001***
High	11.585 (1.6%)	1	10.448	0.001**
Large	4.665 (0.7%)	1	4.207	0.041*
<i>PW</i>	10.532 (1.5%)	3	3.166	0.024*
Cost	3.416 (0.5%)	1	3.081	0.080.
Leis	3.052 (0.4%)	1	2.752	0.098.
Heal	—	—	—	—
Fam	4.064 (0.6%)	1	3.665	0.056.
<i>SD</i>	9.496 (1.4%)	2	4.282	0.014*
Incl	5.104 (0.7%)	1	4.603	0.032*
Safe	4.393 (0.6%)	1	3.961	0.047*
Tech	—	—	—	—
<i>Control variables</i>	99.949 (14.2%)	13	6.934	0.000***
Age	6.440 (0.9%)	1	5.810	0.016*
Marital status	10.040 (1.4%)	1	9.052	0.003**
Education	19.600 (2.8%)	2	8.837	0.000***
Income level	13.710 (2.0%)	1	12.361	0.000***
Area of birth	13.750 (2.0%)	4	3.101	0.015*
Living area	12.040 (1.7%)	1	10.862	0.001**
Experience	24.370 (3.5%)	3	7.328	0.000***
<i>Residuals</i>	551.057 (78.5%)	497		

SoS, sum of squares; DoF, degrees of freedom

“.” *p*-value < 0.1; “\*” *p*-value < 0.05; “\*\*” *p*-value < 0.01; “\*\*\*” *p*-value < 0.001

of items. Specifically, ANOVA disentangles the variability between the group means, which reflects the amount of variance of the dependent variable explained by the group, and the variability within each group, which reflects the internal heterogeneity. Therefore, it is possible to compute the proportion of variance explained by each group of items, which can be interpreted as the relative importance in the prediction of the intention to leave the ecosystem. Among the different typologies of ANOVA, we preferred the type II for two main reasons: variables have the same importance, and no interaction is assumed (see Fox, 2016, Chap. 8 for details).

Four among the selected items regard traditional EE inputs (EE construct). These include *Lead\_1*, related to leadership, *Fin\_2*, related to finance, *Know\_3*, related to knowledge, and *Dem\_2*, related to demand. The estimated coefficient is negative for all these items, indicating that a higher level of the EE input is associated to a lower intention to leave. It can be noted that the t-test is significant at 5% level only for one item, while two items show a borderline significance (*p*-value between 0.05 and 0.1) and the other one has a *p*-value

of 0.128. However, this lack of statistical significance does not mean that the assessment is inconclusive. On the contrary, the fact that items were selected by the adaptive LASSO regularization constitutes evidence of their predictive relevance, thus  $p$ -values higher than 0.05 are likely due to low statistical power (see Heinze et al., 2018). In support of this argument, the F test involving the four items altogether is statistically significant, with a combined explained variance equal to 2.1% of the total. Therefore, Hypothesis 1 is supported.

For what concerns the active presence of successful companies (SC construct), two items were selected: *High\_3*, related to the presence of high growth firms, and *Large\_2*, related to the presence of large firms. The estimated coefficient for both these items is significant and negative, indicating that a higher presence of high growth or large firms is associated to a lower intention to leave. In particular, *High\_3* has a much higher coefficient in absolute value compared to *Large\_2*, suggesting that dynamic, fast-growing businesses are more important for entrepreneur retention in the regions compared to large, but not necessarily growing, businesses. The F test involving the two items altogether is significant as well, and the combined explained variance amounts to 2.3% of the total. Therefore, Hypothesis 2 is supported.

Three among the selected items regard private wellbeing systems (PW construct). These include *Cost\_2*, related to the costs of living, *Leis\_1*, related to leisure services, and *Fam\_1*, related to family facilities. The estimated coefficient is negative for all these items, indicating that a higher sustainability of costs or availability of facilities is associated to a lower intention to leave. However, similarly to items related to traditional EE inputs, the t-tests provide a borderline  $p$ -value but the F test is statistically significant, with a combined explained variance equal to 1.5% of the total. Therefore, Hypothesis 3 is supported.

For what concerns societal development (SD construct), two items were selected: *Incl\_2*, related to accessibility and inclusivity, and *Safe\_2*, related to public safety. The estimated coefficient for both items is significant and negative, indicating that a higher level of inclusivity or public safety is associated to a lower intention to leave. The F test involving the two items altogether is significant as well, and the combined explained variance amounts to 1.4% of the total. Therefore, Hypothesis 4 is supported.

In summary, the selected items altogether explain 7.3% of the total variance, with inputs related to the EE theory and the active presence of successful companies having almost twice the predictive relevance of inputs related to private wellbeing systems and societal development. Instead, control variables explain 14.2% of the total variance. Among them, experience and education result the most important ones, with a percentage of explained variance equal to 3.2 and 2.8, respectively, followed by income level and area of birth that explain each 2% of the total variance. In particular, parameter estimates indicate that a higher income or experience is associated to a lower intention to leave. On the contrary, a higher education level is expected to involve higher chance of leaving. Also, leaving is in average less likely in urban areas than in rural zones, and single entrepreneurs are more prone to leave than married ones, as well as African native entrepreneurs compared to European natives.

## 4.2 Random forests

Permutation variable importance in random forests was performed using R for Statistical Computing (R Core Team, 2024), package ‘party’ (Hothorn et al., 2024). We set a number

of trees equal to 1000 and a number of candidate variables randomly selected at each split equal to 20, corresponding to one third of the number of independent variables as suggested by Breiman (2001). In order to assess the importance of each first and second order construct, all the corresponding items were simultaneously permuted and the difference in root mean squared error (RMSE) was computed. The results are shown in Table 4.

We see that all second order constructs involve a positive difference (increase) in RMSE, which is also significant at the 5% level, as the 95% confidence interval does not contain value zero. The higher predictive relevance is owned by traditional EE inputs (EE construct), which have nearly two and half times the importance of inputs related to private wellbeing systems (PW construct) and more than three times the importance of inputs related to the active presence of successful companies (SC construct) and societal development (SD construct). Therefore, random forests support all research hypotheses as well, although with a different relative importance of constructs compared to adaptive LASSO regression. Such dissimilarity should not be surprising, as the two techniques are substantially different, and thus they differ in how information is extracted from independent variables. For instance, random forests exploit more efficiently the information contained in the items, as control variables have lower importance than all first and second order constructs, while they explain a large proportion of variance in the regression model. However, it must be noted that both analytical techniques agree on the fact that, despite traditional EE inputs are important to predict the intention to leave, other inputs are important as well, especially those related to the active presence of successful companies.

**Table 4** Importance of first and second order constructs in random forests

	$\Delta$ RMSE	
<i>EE</i>	0.113	(0.082, 0.141)
Net	0.002	(-0.002, 0.005)
Lead	0.004	(0.001, 0.009)
Fin	0.002	(-0.002, 0.006)
Tal	0.005	(0.000, 0.010)
Know	0.013	(0.004, 0.022)
Supp	0.009	(0.002, 0.016)
Form	0.000	(-0.002, 0.003)
Cult	0.001	(-0.004, 0.006)
Infr	0.000	(-0.003, 0.004)
Dem	0.008	(0.002, 0.014)
<i>SC</i>	0.033	(0.019, 0.047)
High	0.022	(0.010, 0.033)
Large	0.006	(0.001, 0.012)
<i>PW</i>	0.044	(0.026, 0.063)
Cost	0.002	(-0.004, 0.008)
Leis	0.013	(0.002, 0.023)
Heal	0.004	(-0.001, 0.008)
Fam	0.005	(0.001, 0.010)
<i>SD</i>	0.025	(0.013, 0.039)
Incl	0.010	(0.004, 0.016)
Safe	0.003	(-0.002, 0.008)
Tech	0.006	(-0.002, 0.014)
<i>Control variables</i>	0.009	(0.003, 0.016)

Figures represent the increase in RMSE when all items corresponding to each construct are randomly permuted (1000 trees and 1000 permutations). 95% confidence intervals are shown within brackets

## 5 Discussion

### 5.1 Theoretical contributions

This study advances EE theory by addressing four key limitations: the assumption of static embeddedness, the under-theorization of non-business-related inputs, the need for a refined operationalization of EE inputs, and the scarcity of integrative empirical research on EE inputs. In doing so, we contribute to the literature in several ways.

First, our study challenges the prevailing assumption in EE research that entrepreneurs remain embedded within their ecosystems over time. While EE theory has been widely employed to understand entrepreneurial success, its focus has primarily been on the inputs that facilitate firm creation and growth (Leendertse et al., 2022; Stam, 2015). Our findings highlight that EE boundaries are more permeable than previously assumed, as entrepreneurs consider multiple dimensions of embeddedness when deciding whether to leave their current EE. By focusing on ecosystem leakages, we extend EE theory to account for the role of push factors in entrepreneurial mobility, complementing the dominant focus on pull factors that attract entrepreneurs to new locations (Spigel & Harrison, 2018). In doing so, we align EE theory more closely with broader discussions in economic geography and migration studies that recognize the interplay of economic and social forces in shaping relocation decisions (Roundy, 2019b).

Second, we broaden EE theory by incorporating non-business-related inputs—private well-being systems and societal development—as key determinants of current EE leave. While previous research acknowledges that entrepreneurs are embedded in social structures (Spigel & Harrison, 2018), much of the literature has focused on business-related resources such as finance, networks, and institutional support (Stam & Van de Ven, 2021). Also, recent empirical studies have introduced additional types of inputs (Coad et al., 2025; Herzog et al., 2024). Building on these advancements, we propose integrating two complementary categories: private well-being systems and societal development. Our analysis reveals that each of these diverse input groups significantly contributes to predicting an entrepreneur's relocation to a different ecosystem. This integrated approach highlights the value of incorporating new inputs to capture previously underexplored dimensions of EEs. Our results empirically corroborate that private well-being systems (e.g., cost of living, family support, mental health services) and societal development (e.g., public safety, technological advancement) significantly influence the likelihood of entrepreneurs remaining within the current EE. These findings extend prior work on place-based entrepreneurship (Redhead & Bika, 2022; Schiefer & Van der Noll, 2017), showing that the personal and social embeddedness of entrepreneurs matters alongside traditional inputs.

Third, we propose a novel operationalization of EE inputs, addressing longstanding concerns about conceptual vagueness in EE theory (Brown et al., 2023; Harrison, 2023). Indeed, EE research has been criticized for its broad and sometimes inconsistent definition of inputs, leading to difficulties in empirical measurement (Leendertse et al., 2022). In such vein, this study offers a methodological contribution by presenting a new operationalization of EE inputs. Specifically, we refined the traditional inputs framework by integrating business-related and non-business-related inputs into a coherent measurement model. This model captures the multifaceted nature of entrepreneurial ecosystems by incorporating novel input categories such as private well-being systems and societal development,

alongside traditional EE inputs like networks, finance, and talent. Our approach includes a structured, multi-phase process for item generation, refinement, and validation, ensuring both conceptual rigor and empirical reliability. Our operationalization involved grouping first-order constructs, such as individual inputs, into higher-order categories, thus offering a more structured and scalable approach to measuring EE inputs.

## 5.2 Policy implications

The findings of this study have implications for policymakers seeking to enhance the retention of entrepreneurs within regional ecosystems. Traditional EE policies have focused on strengthening business-related inputs, such as access to venture capital, incubators, and talent networks, assuming that these resources are somewhat predominant in anchoring entrepreneurs within a region (Leendertse et al., 2022; Stam, 2015, 2018). Our results challenge this assumption, showing that non-business factors—such as cost of living, mental health services, public safety, and technological infrastructure—play an equally critical role in entrepreneurial retention.

First, policymakers should be aware of the negative unintended consequences associated with low family and societal embeddedness. Entrepreneurial relocation is not solely driven by the availability of financial capital or network resources but also by broader quality-of-life considerations. In this vein, local governments should recognize that entrepreneurial retention strategies must extend beyond economic incentives to address broader entrepreneurial embeddedness. Policymakers have historically focused on financial incentives—such as tax breaks, grants, and investment matching schemes—to attract and retain entrepreneurs. However, our findings suggest that enhancing societal infrastructure (e.g., urban safety, digital connectivity, and public transportation) is equally important. Policymakers should thus incorporate these considerations into long-term EE development plans, ensuring that regional ecosystems offer a stable and attractive environment for both business and personal life. Addressing these concerns through targeted policies—such as affordable housing initiatives or expanded mental health services—could help retain entrepreneurs who might otherwise seek alternative locations.

Second, policymakers should consider the positive externalities associated with the active presence of successful companies as an anchoring force within EEs. Our findings indicate that the presence of high-growth and large firms significantly reduces the likelihood of entrepreneurs leaving an ecosystem. These firms act as strategic hubs, offering access to market opportunities, mentorship, and financial resources. Policymakers should therefore design incentive structures that encourage established firms to engage with startups through corporate venture capital programs, business accelerators, and local supply chain integration. Policies that strengthen linkages between high-growth firms and the broader entrepreneurial community can enhance structural embeddedness, reducing the appeal of entrepreneurial relocation.

Third, our study suggests that regional policymakers should monitor entrepreneurial ecosystem leakage systematically. While EE theory has primarily focused on ecosystem growth and firm success, our results highlight the importance of tracking entrepreneurial exits as a key performance indicator. Developing data-driven tools to monitor relocation patterns—through surveys, business registration trends, and real-time mobility data—could enable policymakers to identify early warning signs of ecosystem decline. Regions with

high rates of entrepreneurial leakage should conduct targeted exit interviews with departing entrepreneurs to identify specific push factors, allowing for proactive policy adjustments.

### 5.3 Limitations and future research avenues

The present study is not free of limitations. First, the present study inherently focuses on push factors rather than pull factors, which means that while it identifies key drivers of entrepreneurial leave from the current EE, it does not systematically assess what makes prospective EE attractive to relocating entrepreneurs. Future research could adopt a dual perspective, examining both push and pull factors simultaneously to provide a more comprehensive account of entrepreneurial mobility decisions. Moreover, the study employed cross-sectional data, which limits the ability to capture ecosystem dynamics over time. As suggested by Cho et al. (2022), longitudinal analyses in the field of EE could provide deeper insights into the evolution of entrepreneurial ecosystems and their long-term effects. Additionally, the dataset used in this study is relatively small (522 observations), which may limit the representativeness of the findings and calls for larger-scale studies in future research. Particularly, the sampled participants are predominantly entrepreneurs from the United Kingdom and the United States, resulting, for example, in an underrepresentation of emerging economies. The sample also shows a nearly even gender distribution. This significantly differs from global entrepreneurship data, which indicate that men account for a larger share of business owners worldwide. In 2023, for example, 10.9% of women in 45 countries and territories were entrepreneurs, compared to 13.8% of men (Buchholz, 2025). On the other hand, some aspects of the sample are more in line with global trends. Innovation activity, as measured by patent ownership, is relatively low, with an average of 0.18 patents per entrepreneur. This is consistent with broader patterns, where most entrepreneurs do not hold patents (Institute for Women's Policy Research, 2024). Additionally, 71.1% of respondents reside in urban areas, reflecting global entrepreneurship trends that show a concentration of entrepreneurial activity in cities, where access to networks, resources, and markets is greater (Fed Small Business, 2025). Furthermore, whereas our reliance on self-reported data provides direct insights into entrepreneurs' experiences, its limitation lies in the potential subjectivity of individual interpretations. An additional aspect concerns the novelty of the dependent variable. Willingness to leave the current EE is not commonly used in EE research, which may limit comparability with prior studies. Yet, it offers a complementary perspective by highlighting entrepreneurial mobility as an underexplored outcome. Future research could integrate this measure with traditional EE outcomes to provide a more comprehensive understanding of ecosystem dynamics. Besides, future research can further investigate the relationship between embeddedness and retention across individual entrepreneurs and "specific place-based histories" (Stam & van de Ven, 2021, p. 810). A more fine-grained analysis of how historical, cultural, and institutional trajectories shape the embeddedness of entrepreneurs within particular ecosystems could provide valuable insights. Another limitation of our study concerns potential endogeneity issues. Indeed, reliance on observational data limits the ability to establish causality. Endogeneity may arise due to omitted variable bias, reverse causality, or measurement error in self-reported responses. For instance, entrepreneurs who anticipate relocating may perceive ecosystem

conditions differently from those who intend to stay, introducing potential simultaneity bias. Future research could address this concern by employing experimental designs to better disentangle causal mechanisms driving entrepreneurial mobility. Anyway, the inclusion of control variables representing demographic, socioeconomic, geographical, and professional factors should mitigate potential endogeneity issues arising from the omission of factors determining relocation decisions. Finally, the study did not account for the quality and efficiency of formal institutions, such as perceived corruption and the regulatory framework, which might significantly influence entrepreneurship outcomes. Addressing these aspects could strengthen future research in understanding how these external factors shape entrepreneurial relocation decisions.

## 6 Conclusion

EEs are often conceptualized as stable environments where entrepreneurs remain embedded, benefiting from access to finance, networks, and knowledge. However, this assumption overlooks a critical aspect of EE dynamics: entrepreneurs do not always stay. They leave. This study challenges the implicit permanence in EE theory by foregrounding ecosystem leakage—the outflow of entrepreneurs from their original ecosystems due to conditions that erode embeddedness. By extending EE theory through an embeddedness perspective, we move beyond the predominant emphasis on business-related resources and introduce a more comprehensive framework that includes relational, structural, family, and societal embeddedness. Our findings indicate that entrepreneurs do not only respond to traditionally conceptualized EE inputs, but also weigh the broader social and institutional dimensions of their ecosystem. While strong business-related inputs can act as retention mechanisms, they are not sufficient when private well-being systems (e.g., cost of living, mental health services, family support) and societal development factors (e.g., public safety, technological infrastructure) deteriorate. When these non-business dimensions weaken, even ecosystems with abundant entrepreneurial resources struggle to retain talent. This suggests that EE theory must evolve to account for embeddedness erosion—the gradual weakening of ties that leads to departure. For policymakers, this study suggests that retention strategies cannot rely solely on reinforcing traditional entrepreneurial supports. Without attention to the broader conditions that sustain embeddedness, ecosystems risk losing entrepreneurs—not necessarily to more innovative EE, but away from their current environments in search of conditions that meet their professional and personal needs. In a global landscape where talent mobility is increasing, failing to address embeddedness may accelerate entrepreneurial brain drain, weakening the very ecosystems designed to foster innovation, productivity, and growth.

## Appendix

See Tables 5 and 6.

**Table 5** List of items, summary statistics, and factor loadings ( $\lambda$ ) resulting from confirmatory factor analysis

		Mean	Std. dev	Min	Max	$\lambda$
<i>Dependent variable</i>						
Willingness to leave the current EE (Leave)	How likely are you to consider relocation to another region's entrepreneurial ecosystem, thereby leaving your current ecosystem, within the next three years?	2.762	1.518	1.000	7.000	–
<i>EE theory's inputs (EE)</i>						
Net-works (Net)	In my region, online platforms for local entrepreneurs are active and provide valuable connections	4.596	1.500	1.000	7.000	0.909
	In my region, mentorship programs are readily available and match new entrepreneurs with experienced ones	3.875	1.609	1.000	7.000	0.913
Leadership (Lead)	In my region, there are successful entrepreneurs who serve as role models	4.822	1.476	1.000	7.000	0.882
	In my region, community leaders frequently organize forums and discussions on entrepreneurship	3.977	1.605	1.000	7.000	0.903
Finance (Fin)	In my region, ventures have access to a variety of funding sources, including government grants, angel investors, and venture capital	4.379	1.556	1.000	7.000	0.881
	In my region, local banks offer products tailored specifically to the needs of startups	4.169	1.579	1.000	7.000	0.739
	In my region, financial support is available for different stages of business development, from seed to scale	4.393	1.489	1.000	7.000	0.894
Talent (Tal)	In my region, the local job market has a diverse pool of highly skilled individuals	4.554	1.642	1.000	7.000	0.787
	In my region, universities have strong ties with the entrepreneurial sector, offering relevant programs	4.370	1.470	1.000	7.000	0.772
	In my region, talent retention rates are high due to attractive working conditions in the entrepreneurial sector	3.810	1.539	1.000	7.000	0.849
Knowledge (Know)	In my region, there is a high level of collaboration between businesses and local research institutions	4.119	1.537	1.000	7.000	0.831
	In my region, information about market trends and industry insights is readily accessible through local knowledge hubs	4.111	1.520	1.000	7.000	0.857
	In my region, regular workshops and seminars are held to disseminate latest business and technological advancements	4.052	1.625	1.000	7.000	0.867
Support services (Supp)	In my region, local support services effectively help startups navigate legal and regulatory requirements	4.059	1.560	1.000	7.000	0.878
	In my region, business incubators and accelerators have a proven track record of success in supporting new businesses	3.989	1.474	1.000	7.000	0.888
	In my region, consulting and advisory services are readily available at subsidized rates for startups	3.889	1.527	1.000	7.000	0.861
Formal institutions (Form)	In my region, the legal environment is optimized and adds to the bureaucratic burden on new businesses	4.762	1.362	1.000	7.000	0.807
	In my region, public-private partnerships are actively promoted and facilitate business development	4.011	1.080	1.000	7.000	0.702

Table 5 (continued)

		Mean	Std. dev	Min	Max	$\lambda$
Culture (Cult)	In my region, entrepreneurship is considered a prestigious career choice	4.716	1.542	1.000	7.000	0.753
	In my region, the local culture celebrates entrepreneurial success and tolerates business failures as part of the learning process	4.314	1.558	1.000	7.000	0.879
	In my region, there is widespread public trust in the contributions of entrepreneurs to economic and social welfare	4.259	1.405	1.000	7.000	0.848
Infrastructure (Infr)	In my region, transport infrastructure effectively supports the distribution and logistics needs of businesses	4.312	1.669	1.000	7.000	0.858
	In my region, the digital infrastructure meets the high-speed requirements of modern businesses and the physical infrastructure is being continuously updated to keep up with technological advancements	4.266	1.515	1.000	7.000	0.881
Demand (Dem)	In my region, local consumer demand for innovative products and services is strong and growing	4.705	1.382	1.000	7.000	0.739
	In my region, market research services and data analytics are accessible to help businesses identify and meet customer needs	4.477	1.452	1.000	7.000	0.852
	In my region, the economic policies are in place to promote and protect market competitiveness for new businesses	4.182	1.415	1.000	7.000	0.828
<i>Active presence of successful companies (SC)</i>						
Active presence of high-growth companies (High)	In my region, there are numerous high-growth firms that stimulate local economic development	4.065	1.471	1.000	7.000	0.878
	In my region, success stories of rapidly growing firms are common and well-publicized	3.847	1.568	1.000	7.000	0.832
	In my region, high-growth firms contribute significantly to job creation	4.333	1.452	1.000	7.000	0.870
Active presence of large companies (Large)	In my region there many large companies are active	4.910	1.570	1.000	7.000	0.835
	In my region, large firms often act as clients or partners to local startups	3.954	1.479	1.000	7.000	0.847
<i>Private well-being systems (PW)</i>						
Costs of life (Cost)	In my region, the cost of living is reasonable relative to the opportunities for entrepreneurship	3.571	1.710	1.000	7.000	0.906
	In my region, housing is affordable for entrepreneurs at various income levels	3.238	1.825	1.000	7.000	0.896
	In my region, daily expenses (e.g., food, utilities) are manageable even for new entrepreneurs	3.632	1.626	1.000	7.000	0.879
Leisure time (Leis)	In my region, the community values and supports a balanced lifestyle	4.619	1.424	1.000	7.000	0.796
	In my region, there are numerous leisure and recreational activities available for entrepreneurs	4.567	1.591	1.000	7.000	0.840
	In my region, cultural and social events that enrich quality of life are promoted	4.950	1.372	1.000	7.000	0.819

**Table 5** (continued)

		Mean	Std. dev	Min	Max	$\lambda$
Mental health and well-being services (Heal)	In my region, there are accessible mental health services and a culture of well-being	4.186	1.769	1.000	7.000	0.817
	In my region, a work-life balance is concretely valued and actively supported	4.362	1.642	1.000	7.000	0.868
	In my region, there are initiatives in place to prevent burnout among entrepreneurs	3.439	1.606	1.000	7.000	0.857
Family facilities (Fam)	My region provides excellent family facilities for working parents	3.732	1.629	1.000	7.000	0.869
	In my region, schools and educational institutions are supportive of the needs of entrepreneurs' families	3.885	1.548	1.000	7.000	0.853
	In my region, there are ample recreational facilities for families within the community	4.822	1.537	1.000	7.000	0.709
<i>Societal development (SD)</i>						
Accessibility and inclusivity (Incl)	In my region, programs and resources to support entrepreneurship are accessible to all, regardless of language, mobility, or other barriers	4.146	1.446	1.000	7.000	0.886
	In my region, local networking events are held in venues that are accessible and welcoming to everyone	4.557	1.435	1.000	7.000	0.898
Public safety (Safe)	In my region, I feel safe at any time of day	4.985	1.606	1.000	7.000	0.822
	In my region, public safety concerns never deter me from attending business events or seeking new opportunities	5.052	1.582	1.000	7.000	0.863
Technological advancement (Tech)	In my region, local businesses are quick to adopt new technologies and emerging technological trends	4.477	1.421	1.000	7.000	0.901
	In my region, investment in the latest technology trends is seen as a priority for economic growth	4.262	1.481	1.000	7.000	0.901

**Table 6** Validity indices for constructs resulting from confirmatory factor analysis: composite reliability index (CRI), average variance extracted (AVE), and heterotrait-monotrait ratio (HTMT)

		CRI	AVE	HTMT
EE	Net	0.907	0.830	0.754
	Lead	0.887	0.797	0.698
	Fin	0.878	0.707	0.697
	Tal	0.845	0.645	0.796
	Know	0.888	0.725	0.818
	Supp	0.908	0.767	0.803
	Form	0.727	0.572	0.582
	Cult	0.867	0.686	0.657
	Infr	0.861	0.756	0.667
	Dem	0.849	0.653	0.768
HL	High	0.895	0.740	0.737
	Large	0.828	0.707	0.615
PW	Cost	0.923	0.799	0.365
	Leis	0.859	0.670	0.722
	Heal	0.884	0.718	0.710
SD	Fam	0.853	0.661	0.682
	Incl	0.886	0.796	0.700
	Safe	0.831	0.711	0.300
	Tech	0.896	0.811	0.727

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## Declarations

**Conflict of interest** The authors declare no competing interests.

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