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A meta-analysis of entrepreneurial ecosystem elements and entrepreneurial activity

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Abstract This meta-analysis examines the relationship between entrepreneurial ecosystem (EE) elements and regional entrepreneurial activity (EA). An extensive literature search is performed to identify quantitative studies covering EE elements and EA at the regional level (257 studies) and to extract relevant data (2,241,813 observations). To synthesize the findings, we group the potential antecedent variables based on Stam's (*European Planning Studies*, 23(9):1759–1769, 2015) EE framework. The results show large differences in the effect sizes and relevance of EE elements. Based on the empirical results, three relevant elements underlying all EEs are identified: demand, talent, and finance. Our results remain robust after using different methods for variable grouping, applying meta-analytic regression, and

controlling for country, publication specifics, and grouping errors. Propositions for building an EE theory are derived, and future research opportunities are discussed, as well as policy implications.

Plain English Summary A meta-analysis of entrepreneurial ecosystems and their effects on entrepreneurial activity shows that elements of entrepreneurial ecosystems vary substantially in their importance for different kinds of new business formation. Entrepreneurial ecosystems (EEs) have grown in importance in entrepreneurship research over the last decade, attracting significant attention from both researchers and practitioners. One reason for this high level of interest is that the concept of EE provides a fresh lens for describing how entrepreneurial activity (EA) varies between locations, an issue that scholars have long examined. It has been proposed that many elements of EEs join together to form a regional ecosystem generating EA as its output. It is unclear, however, whether all presented EE elements are relevant for EA, as well as how relevant they are in relation to each other. This study aims to investigate EA through the lens of EE and examines the EE elements that have been considered in previous empirical research. It investigates the existence and strength of links between EE elements and EA before identifying essential EE elements to further advance EE theory development. This paper adopts an evidence-based research approach and uses meta-analysis to identify

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antecedents of EA at the regional level. Our results show that demand, finance, and talent element measures are important antecedents for general EA, while culture, knowledge, and support services are important antecedents for productive EA. This contribution is important for empirical researchers and policymakers alike. Researchers can use the provided information to refine their empirical models, while policymakers can develop and implement instruments that stimulate the desired EA type within an ecosystem. Moreover, the study advances the theoretical modeling of EE regarding core components depending on the type of EA.

Keywords Entrepreneurial ecosystem · Meta-analysis · Entrepreneurial activity · Context · Environment · Regional entrepreneurship

JEL Classification L26 · M13 · R1 · R11

1 Introduction

Over the past decade, entrepreneurial ecosystems (EEs) have become an important concept in entrepreneurship research, attracting significant attention from both scholars and practitioners (Acs et al., 2014; Brown & Mawson, 2019; Lafuente et al., 2022; Wurth et al., 2021). One reason for this widespread attention is that the concept of EE offers a new lens for explaining how entrepreneurial activity (EA) differs across regions (Autio et al., 2014; Audretsch, 2015; O'Connor et al., 2018; Wurth et al., 2021; Fischer et al., 2022), a question that has long been investigated by researchers from multiple disciplines (Fernandes & Ferreira, 2022; Kansheba & Wald, 2020; Maroufkhani et al., 2018). It has been argued that a variety of elements (also described as actors and factors, pillars, or conditions) collectively form an ecosystem in a given region that produces EA as an output (Acs et al., 2014; Spigel, 2017; Stam, 2015).

The EE concept is eclectic in that it integrates relevant parts of various literature streams—such as entrepreneurial context (Welter, 2011), business and innovation ecosystems (Scaringella & Radziwon, 2018), or spatial approaches (e.g., clusters) (Delgado et al., 2010)—to understand where, how, and why EA takes place. The EE concept is explicitly systemic and sees entrepreneurs not only as an output of the

ecosystem but also as a core part of it (Stam, 2015). This differentiates EE from other systemic, spatially delineated approaches, such as regional innovation systems or clusters, which have been previously used to explain EA (Acs et al., 2017; Wurth et al., 2021). The core benefits of the EE concept include the systemic integration of relevant literature streams accounting for the context in which entrepreneurship takes place, and the explicit focus on the entrepreneur and EA as an output.

The EE concept, however, also has some shortcomings that have impeded the construction of a comprehensive EE theory to explain EA (Abootorabi et al., 2021; Alvedalen & Boschma, 2017; O'Connor & Audretsch, 2023; Wurth et al., 2021). Among the most important issues that hinder the formulation of a coherent EE theory is the plethora of elements, such as demand, physical infrastructure, networks, and culture, included in current EE frameworks (Leendertse et al., 2022; Spigel & Harrison, 2018; Stam & Spigel, 2018; Wurth et al., 2021). The inclusion of these elements is largely presented as self-evident without a deeper theoretical discussion as to whether they are relevant to EA, let alone how relevant they are in relation to each other. This lack of dialogue renders the existing research unsatisfactory, given that the EE literature also highlights the strong empirical foundations of these elements. Recent quantitative EE studies have often used variables to assess these EE elements that are anything but new in research on antecedents of EA (Audretsch & Belitski, 2017; Hechavarría & Ingram, 2019; Stam, 2018; Yan & Guan, 2019). The broad collection of antecedents of EA, identified through a bottom-up and practice-based empirical methodology (Audretsch & Belitski, 2021; Spigel & Harrison, 2018), still require investigation for causal linkages before they can be acknowledged as essential EE elements and EE theory development can advance.

In addition to this lack of conceptual and empirical grounding of relevant EE elements, heterogeneity regarding the focal EE output further hampers the theoretical integration and advancement of the EE concept. The EE literature is not clear regarding the type of entrepreneurship that these ecosystems foster. EE research tends to use general measures of EA, such as new business formation (Audretsch & Belitski, 2017; Content et al., 2020), while, at the same time, explicit measures of productive EA, such

as data on venture capital (VC)–backed ventures, are also applied to analyze the EE output (Stam & van de Ven, 2021; Leendertse et al., 2022). Scholars argue that productive entrepreneurship develops in different environments than other, less impactful types of EA (Acs, 2011; Audretsch et al., 2022; Baumol, 1990). An EE that fosters productive EA might be differently constituted than an EE that leads to general EA. Furthermore, adequately measuring types of EA remains a key task for entrepreneurship research (Henrekson & Sanandaji, 2014).

Motivated by these research gaps, we adopt an evidence-based research approach (Frese et al., 2014) and conduct a meta-analysis on the antecedents of productive and general EA at the regional level. Synthesizing prior findings through meta-analysis can help evolve knowledge in a given field and identify new pathways for future research (Bacq et al., 2021; Rauch, 2020). Our meta-analysis builds on decades of research on the antecedents of EA, allowing us to comprehensively synthesize extant empirical findings into one EE framework and provide effect sizes for each potential element within it. To categorize relevant independent variables, we rely on the EE framework of Stam (2015). We explicitly focus on the relationships between each EE element and the two types of EA (i.e., productive and general) at the regional level. Both types of EA are considered because Stam's model and other EE models have also been widely applied in the literature to explain the emergence of other kinds of EA and the vast body of empirical research on EEs uses a variety of EA output measures (Ahmad & Hoffmann, 2012; Audretsch & Belitski, 2017; Henrekson & Sanandaji, 2014, 2020). These EA indicators do not always fit the broad definition of productive EA and may lead to an imprecise empirical foundation of the antecedents of EA. Therefore, this meta-analysis uses several existing measures of EA to capture some aspects of "reality" (Henrekson & Sanandaji, 2014, p. 755) in order to identify antecedents of EA through the lens of EE. Lastly, it should be noted that this study only considers EEs and does not address business, innovation, and EE sub-ecosystems or spatial approaches.

This article contributes to the development of an EE theory by summarizing the existing empirical findings prevalent in EE research, identifying the overall directions and magnitudes of the effects of EE elements on EA. Various EE literature reviews have

shed light on the diversity of relevant definitions and the theoretical foundations of the approach, highlighting the importance of understanding the causal mechanisms of EEs in developing an EE theory (Cao & Shi, 2021; Credit et al., 2018; Malecki, 2018). Accordingly, a consistent theoretical foundation and empirical basis need to be established (Wurth et al., 2021). We argue that such an empirical basis for developing a coherent EE theory does not yet exist. While there are hundreds of empirical studies on the antecedents of regional EA, there has not been a comprehensive integration of these studies into an EE framework. Analyzing which elements are relevant and detecting their effect sizes are necessary and overdue first steps. By taking these steps, we comprehensively address the question of the relevance of individual EE elements, which has been a constant concern in the literature and a key hindrance to theory development (Alvedalen & Boschma, 2017; Spigel, 2016; Spigel & Harrison, 2018; Wurth et al., 2021). In order to gain a better understanding of the individual EE elements, we further differentiate between productive EA and general EA. This differentiation helps to identify the impact of individual EE elements on types of EA, providing further guidance in the endeavor to shift the EE concept toward an EE theory.

2 State of the research on entrepreneurial ecosystems

2.1 The EE concept

Entrepreneurial ecosystems are a concept that has recently experienced increasing popularity within entrepreneurship research, originating from two established research streams (Cao & Shi, 2021; Cavallo et al., 2019; Malecki, 2018). The first of these streams is the one on entrepreneurial context (Autio et al., 2014; Welter, 2011), where the EE concept is rooted in management studies on the spatial and socioeconomic environments in which entrepreneurship takes place (Dubini, 1989; van de Ven, 1993). The second stream is on location and localization (agglomeration) economics, which highlights the importance of spatial proximity for learning, innovation, and productivity (Arrow, 1962; Jacobs, 1969; Marshall, 1890; Romer, 1986). The core of the EE concept is the notation of entrepreneurship within

an ecosystem, which is a concept rooted in ecology, where the interactions of organisms and the environment play a key role (Kuckertz, 2019; O'Connor et al., 2018). Like ecological ecosystems, EEs have a spatial dimension, existing in spatially delineated territories in which actors and other factors interact (Stam & Spiegel, 2018). An EE can be defined as “a set of interdependent actors and factors coordinated in such a way that they enable productive entrepreneurship within a particular territory” (Stam, 2015, p. 1765). With this systemic interpretation of the entrepreneurial context, EEs followed preceding theories on systemic territorial development (Qian & Acs, 2023)—such as clusters (Cooke, 2001; Delgado et al., 2010) and regional innovation systems (RIS) (Asheim et al., 2011; Cooke et al., 1997)—which developed independently from entrepreneurship research but were later applied to explain entrepreneurship (Delgado et al., 2010; Neck et al., 2004; Qian et al., 2013; Ylinenpää, 2009).

As the systematic comparison of the RIS and EE approaches by Qian and Acs (2023) shows, the RIS heritage within the EE approach is still visible in several commonalities between the concepts, like their key components and their emphasis on the relevance of the regional knowledge base. RIS and EE share a systemic view that converges in knowledge-intensive entrepreneurship, which essentially relies on technological variety and knowledge intensity (Radošević & Yoruk, 2013). The key outcome of RIS (i.e., product and process innovation) can be seen as a precursor to the key outcome of EE (i.e., productive EA). EEs can also be seen as a subsystem of RIS, reflecting the component of RIS that is related to the entrepreneurial usage of innovations for new business formation (e.g., Han & Ko, 2017; Radošević & Yoruk, 2013; Sternberg, 2007). Another similarity between RIS and EEs that emerges from their systemic nature is their propensity to fall prey to some kind of system failure. According to Stam (2015), a system failure in an EE is caused by insufficient availability of necessary elements, as well as non-optimal interactions between these elements, and how policy intervention can solve these issues. Pyka et al. (2019) provide an exemplary set of policy interventions in RIS to address system failures with implications for entrepreneurship, finding (co-)evolutionary processes and self-enforcing dynamics that further highlight the importance of the systemic view of RIS and EE (for

the system dynamics of EE see also Haarhaus et al., 2020).

At this point, it is necessary to point to the recent emergence of EE subsystems (e.g., digital and sustainable EE) in the literature, which are specific systems and components of the overall or general EE, the theoretical foundation of the EE needs to be built as a general framework. In this regard, the digital EE is specified as a more specialized system with the purpose of explaining digital ecosystems and digital EA. In this context, the digital EE has specific configurations, functions, and dimensions that require further (prerequisite) resource endowments (for instance the specific demand for digital skills in human capital and ICT infrastructure) in comparison to general EE and general EA (Bejjani et al., 2023; Sussan & Acs, 2017). Another more complex subsystem is the sustainable EE with two distinct purposes: On the one hand, the endowments should not be used up by EA to enable sustainability (Theodoraki et al., 2022; Volkmann et al., 2021). On the other hand, sustainable EEs focus on those EE elements that positively influence sustainability-oriented EA (Crecente et al., 2021; Theodoraki et al., 2022; Volkmann et al., 2021). Digital as well as sustainable EEs are important subsystems of the general EE and need to be incorporated into a unifying EE theory. In the present meta-analysis, the focus is on the general EE elements rather than specific subsystems of EEs, given that first a general consensus about the essential EE elements needs to be reached.

2.2 Advantages of the EE concept

We argue that the EE concept in its current state provides a fruitful basis for the development of an EE theory for two reasons. First, it explicitly considers the entrepreneur to be not only an output but also an input of the system, differentiating the EE concept from clusters or innovation systems (Stam, 2015). This is crucial for understanding EA in a given territory—the relevance of role models (Bosma et al., 2012), serial entrepreneurs (Parker, 2013), and network ties (Shane & Cable, 2002) for new venture formation and success has been previously established; thus, a theory for explaining EA rates should include the presence and relevance of other entrepreneurs. The inclusion of entrepreneurs as an input also adds a dynamic, intertemporal perspective, aligning with

evidence suggesting that historic levels of EA influence present EA (Fritsch & Wyrwich, 2014). Scholars have also recently argued that the “where” in entrepreneurship theory needs to take into account the interdependencies between entrepreneurs and their environment over time (Baker & Welter, 2021).

Second, the EE concept includes every actor and factor of the entrepreneurship context and its interdependencies. It consists of a wide range of elements that could potentially influence EA, such as entrepreneurship support services, networks of entrepreneurship-related actors, financing, accumulated knowledge within a region, and domestic market size (Stam, 2015). The EE concept not only integrates these elements into one holistic framework but also explicitly considers their interdependencies. For example, when looking at support services, accelerators might lead to both mentoring and networks (Chan et al., 2020), i.e., one EE element (support services) has a direct relation to other elements (networks, leadership). Bringing together both of these highly relevant aspects of the entrepreneurship context makes the EE concept original and enables researchers to integrate and reconsider previous findings.

2.3 Current disadvantages and gaps regarding the EE concept

A disadvantage of the current state of EE concepts, which explicitly aim at explaining EA in a given territory, is that they do not fulfill the requirement to provide generalizable principles for the causal mechanisms behind this (Corley & Gioia, 2011). To move beyond a concept, EE theory must include precise definitions of its boundaries (phenomenological and spatial); be applicable for most, or ultimately, all regions that have or could have EA; and provide clear explanations of the causal mechanisms underlying the system that ultimately lead to EA as an output. The approaches and results of existing empirical studies on EE, however, are inconsistent in several respects. One such divergence in empirical findings on EEs relates to which elements need to be present in an EE to stimulate high levels of EA. A frequent assumption is that all elements of an EE model need to be sufficiently present to stimulate high levels of EA (Schrijvers et al., 2023). A competing assumption is one of substitutability, which suggests that some strong EE elements might compensate for other

weaker elements so that not all elements need to be equally present to stimulate high levels of EA (Schrijvers et al., 2023; Spigel, 2017). While results from some empirical studies tend to support the former completeness logic (e.g., Lafuente et al., 2022; Schrijvers et al., 2023), others provide support for the latter “the-more-the-merrier” logic (e.g., Audretsch & Belitski, 2017; Torres & Godinho, 2022).

There is also inconsistency in measuring EE elements and, thus, the interpretations that can be derived from them. One set of studies applies composite indices that comprise all elements of the respective EE framework to examine the relationship between EEs and EA (e.g., Acs et al., 2014; Acs et al., 2018; Stam & van de Ven, 2021; Lafuente et al., 2022). Another set of studies uses a decomposed set of EE elements to study their impact on EA without aggregating the elements into one value (e.g., Acs et al., 2013; Armington & Acs, 2002; Audretsch & Belitski, 2021). This measurement approach is similar to previous research on the influences of different groups of EA antecedents in a given spatial area, which has often used variables and variable sources that are similar or identical to those used in the EE literature. Examples of such studies include Armington and Acs (2002), Audretsch and Belitski (2013), Stenholm et al. (2013), and Stuetzer et al. (2014). The results of the different operationalizations lead to vastly different interpretations. While the composite index approach allows conclusions to be made about the overarching effects of EEs on EA, other operationalizations make inferences regarding the relative impact of each EE element on EA, which makes it difficult to compare and integrate results from these varied approaches. Moreover, there is also a large variation in the factors that are considered to be elements of EE (e.g., Audretsch & Belitski, 2017; Isenberg, 2010; Mason & Brown, 2014; O'Connor & Audretsch, 2023; Roundy et al., 2017; Spigel, 2017; Stam, 2015). Results for individual EE elements are ambiguous across studies regarding their association with EA (see Appendix 1, Table 4 and Supplementary Material F).

Further, the EE concept lacks a clear empirical foundation, which would offer a more rigorous framework and methodology for measuring and comparing entrepreneurial ecosystems (Audretsch et al., 2019; Brush et al., 2019; Scaringella & Radziwon, 2018; Sternberg et al., 2019). The lack of a clear and consistent method of entrepreneurial ecosystem measurement hinders the comparison and generalization

of findings across different contexts and levels of analysis (Alvedalen & Boschma, 2017; Brown & Mason, 2017; Scaringella & Radziwon, 2018). While EE frameworks are widely used, there is not a coherent definition as to what these frameworks should contain. Scholars use EE frameworks quantitatively to “test” these frameworks and their elements—as if there is a universal EE theory for which the frameworks and their elements can be taken for granted (examples include Stam & van de Ven, 2021; Leendertse et al., 2022). However, it is not clear if all assumptions within these frameworks do apply and, in particular, if the elements that they consist of are meaningful. Scholars have provided varied lists of the “elements” or “pillars” that make up these frameworks, often guided by practitioners’ perceptions and recommendations (Isenberg, 2010; Feld, 2012; World Economic Forum, 2013). It is not clear, however, which of these elements, if any, are actually significantly related to EA. For example, although there are diverging findings within the literature regarding the influence of infrastructure on EA (Audretsch et al., 2015; Bennett, 2019), infrastructure is a key element of current EE frameworks (Wurth et al., 2021). Developing a sound empirical basis for each element will help provide a foundation for examining the role of each element and its interdependencies. Only then can explanations of the causal mechanisms that describe (a) the relationships between regional EE elements and EA and (b) the relationships between the regional EE elements be fully developed.

We argue, however, that the EE concept, when viewed through a theoretical lens, is not yet useful. It has most often been operationalized in quantitative empirical studies that use well-established variables to assess some type of EE quality or ranking and regress EA on them (e.g., Stam & van de Ven, 2021; Audretsch & Belitski, 2021; Leendertse et al., 2022) or as a concept for qualitatively researching EEs in particular cities or regions (e.g., Kapturkiewicz, 2022; Motoyama & Knowlton, 2017; Spigel, 2017). Until now, the EE concept has offered little novelty in terms of explaining and testing the influencing factors of EA or the causal mechanisms in any type of entrepreneurship system (or entrepreneurial environment). Its two core strengths—i.e., integrating the entrepreneur and comprehensiveness regarding the factors in the entrepreneur’s context—have not been well-specified or leveraged thus far. There is a lack of

a strong theoretical foundation and a causal explanation of how entrepreneurial ecosystems work, as well as the mechanisms and processes that link the ecosystem components to each other and to entrepreneurial outcomes (e.g., Alvedalen & Boschma, 2017; Brown & Mason, 2017; Spigel & Harrison, 2018; Schäfer & Mayer, 2019).

Moreover, analogous to Audretsch et al.’s (2019) differentiation of other systemic views, ecosystem approaches to entrepreneurship exist at the local/regional level (Audretsch & Belitski, 2017; Zhang & Roelfsema, 2020), state level (Content et al., 2020; Stam & van de Ven, 2021), and the country level (Acs et al., 2014; Hechavarría & Ingram, 2019). Thus, there are several gaps that currently exist in research on EEs, such as the unclear novelty compared to previous approaches (Scaringella & Radziwon, 2018), inconsistent implications for policy (Brown & Mason, 2017), and the need for the development and use of clear and multi-scalar approaches with quantitative evidence for individual elements (Alvedalen & Boschma, 2017; Wurth et al., 2021). Furthermore, EE studies often limit their focus to either general measures of EA (Content et al., 2020) or productive EA (Leendertse et al., 2022). Research shows that past rates of EA in regions predict future rates of EA and influence entrepreneurial attitudes and innovation in later periods (Fritsch & Wyrwich, 2014; Fritsch et al., 2019). The conceptual EE literature focuses on productive EA as the output of ecosystems (Wurth et al., 2021) but emphasizes the importance of all entrepreneurs and their interactions (Spigel, 2017). Thus, an EE theory needs to take into account these differences among types of EA and distinguish between the EE elements that are generally relevant for EA or relevant only for a specific type of EA.

2.4 Meta-analysis as the basis for the further development of the EE concept

Addressing the previously identified gaps is directly related to assessing the elements of EEs. To our knowledge, no comprehensive, empirical analyses have been performed to determine which of these elements are relevant. Hence, a comprehensive synthesis of the empirical studies analyzing EA determinants will facilitate the identification of the elements within specific EE frameworks that have significant relationships with EA and are most likely to be part of

a generalizable EE framework. One possible outcome of this assessment could be broad empirical support for the relevance of all the EE elements. The second possible outcome is that some elements within current EE frameworks are not related to EA. If the second outcome is the case, building an EE theory would require carefully assessing the theoretical and empirical origins of the EE elements that are not directly relevant. If the reasoning for its initial inclusion is unclear, such an element may be excluded from the core list of elements in EE theory. If an element has a strong theoretical foundation but is non-significant in a comprehensive meta-analysis, this would suggest that there is more to its inclusion, i.e., we cannot empirically assess the element using previous studies and methods (Rauch & Frese, 2006).

To shift the EE from a somewhat vague concept with generic empirical contributions to a contextual theory for entrepreneurship, an empirical foundation that integrates not only new EE studies but also other studies on the antecedents of EA is needed. We argue that statistically integrating prior quantitative findings into the EE concept is the first step toward building an EE theory. This could prevent it from maintaining blind assumptions for theory building (Gartner, 2001). Rather, the assumptions of the elements of which EEs would be empirically clear. Research following this initial step could be more precise and rigorous regarding which elements should be considered and how they should be empirically tested. Ultimately, this will build a basis for understanding the causal mechanisms underlying the relationships between the EE elements and the EA outcomes.

This study builds on the EE framework of Stam (2015) as a conceptual basis for grouping relevant variables. However, we would like to note that the role of Stam's (2015) framework in grouping the plethora of variables used in empirical EE research does not imply that we build on this framework for other, especially theoretical, purposes. Rather, we use it to standardize categories, merging and integrating variables into these categories across frameworks for comparability. Stam's framework is based on an integration of previous research and consists of ten EE elements that are collectively thought to produce productive EA as an output (Stam, 2015). These elements are similar to those found in other frameworks and empirical EE assessments (Acs et al., 2015; Autio et al., 2018; Iacobucci & Perugini, 2021;

Spigel, 2017). This framework has been broadly considered within the EE literature and has been used as a foundational framework in many empirical studies (e.g., Iacobucci & Perugini, 2021; Ibrahimova & Moog, 2023; Leendertse et al., 2022; Schrijvers et al., 2023). Moreover, the framework is chosen because it integrates the findings in the literature on the role of geographic context in entrepreneurship, is well documented, and provides examples as well as descriptions of elements and variables (Ibrahimova & Moog, 2023; Schrijvers et al., 2023). Furthermore, the framework consists of several unique dimensions creating multiple constructs to allow for in-depth analysis of the elements, rather than aggregating all variables into selective theoretical constructs.

2.5 The meta-analytic approach

Meta-analysis is the "statistical analysis of a large collection of analysis results from individual studies for the purpose of integrating the findings" (Glass, 1976, p. 3). A frequently used statistical technique, it combines the results of multiple individual scientific studies on the same topic to examine the accumulated findings (Gurevitch et al., 2018). A meta-analysis can help take stock of the existing evidence (e.g., to look at the "true" effect of an independent variable on a dependent variable), identify sources of variation and heterogeneity among studies, and assess the quality and reliability of the findings (Gurevitch et al., 2018; Schwab, 2015). It can also reveal new insights and patterns that may not be apparent in individual studies (Gurevitch et al., 2018). According to Gurevitch et al. (2018), the method is used in many different research domains and is essential for progress in science. In entrepreneurship research, the meta-analysis approach is used to advance our understanding of the phenomenon of entrepreneurship in different settings (Rauch & Frese, 2006, 2007; Rauch et al., 2009; Schwens et al., 2018) and helps to quantitatively synthesize prior empirical research (Rauch, 2020; Schwab, 2015).

Meta-analyses commonly follow the same set of key steps (Aguinis et al., 2011; Cooper et al., 2019; Steel et al., 2021). First, the analysis identifies a phenomenon of interest and formulates relevant search strings to find the pertinent literature. This literature is then screened for eligibility based on inclusion and exclusion criteria and, if included in the data sample

for the meta-analysis, coded accordingly. The second step consists of data transformation and preparation in which the characteristics of each study must be evaluated and normalized (e.g., effect size measures, publication bias). The third step is the actual analysis, which is based on a specified estimation approach to obtain the average effect size, determine the robustness of the results, and perform a sensitivity analysis of the identified average effect size. Within this stage, it is common to perform a moderator and/or mediator analysis. The last step is the reporting of results.

While meta-analyses offer many advantages and opportunities, as mentioned above, they also have some disadvantages. The clearest limitations of the method lie in its *ex post* design. The meta-analysis is bound to its input studies and is thus dependent on the variables and information provided in these empirical studies. If not properly addressed, a lack of transparency and missing information in collected studies, publication biases, and sample estimation weights (representation of the population) can be the biggest challenges within a meta-analysis (Cooper et al., 2019; Steel et al., 2021). Additionally, the quality of the data depends on the quality of the primary studies included in the meta-analysis (Cooper et al., 2019; Steel et al., 2021). Further advantages and limitations of meta-analysis as a research synthesis method are extensively discussed in Cooper et al. (2019). In this paper, the meta-analytic approach enables us to generalize findings from large groups of heterogeneous studies with the goal of (1) identifying the overall design of the EE framework at the regional level and (2) analyzing the relevance of regional EE elements as antecedents of EA.

3 Method

3.1 Sampling and search strategy

We began by screening recent systematic literature reviews to identify relevant key search terms for our meta-analysis (e.g., O'Connor et al., 2018; Kansheba & Wald, 2020; Wurth et al., 2021; Fernandes & Ferreira, 2022; Maroufkhani et al., 2018). These initial keywords were extended with synonyms to obtain a large initial sample of articles to assure completeness and limit potential sample selection biases (Hiebl, 2021). The final list of search terms included

all possible combinations, variations, and synonyms of the terms “entrepreneur” and “ecosystem” in combination with variations of the terms “environment,” “system,” “support,” “entry,” and activity (see Appendix 2, Table 5 for the research strategy). We used the academic search engines Scopus, Web of Science, and ProQuest to identify relevant publications (the latter includes dissertations, conference proceedings, and additional unpublished studies). Because of the absence of other meta-analyses in this field, our search was not restricted to a specific time period.

Our search strategy (Fig. 1) resulted in 9435 studies, the full text of which was then screened to determine relevance and examine their reported quantitative results. To be eligible for inclusion, empirical studies were required to contain at least one measurement of EA (dependent variable of this meta-analysis) and one variable that could be associated with the EE framework of Stam (2015) (independent variable of this meta-analysis). Several different ways to measure the EA output metric of an entrepreneurial process have been identified within the literature (Ahmad & Hoffmann, 2012; Henrekson & Sanandaji, 2014). We included studies that reported at least one of the following EA measures: self-employment rates, new firm formation, churn rates, number of start-ups, and total early-stage entrepreneurial activity. The other relevant variables from these primary studies are measures that can be assigned to one of the EE elements of Stam (2015). These included the elements of “Networks,” “Leadership,” “Finance,” “Talent,” “Knowledge,” “Support Services/Intermediaries,” “Formal Institutions,” “Culture,” “Physical Infrastructure,” and “Demand.” The criterion for variable extraction was that the variable was attributed to spatially delineated territorial units to build a large initial database of antecedents of EA and gain initial insights.

After screening the initial 9435 papers based on these criteria, 443 studies remained. A forward and backward citation query of the remaining studies resulted in a second screening of 11,019 additional papers, which were also screened and of which 149 were retained. During the screening process, we initially filtered out studies with missing data but contacted their authors. Of 56 contacted authors, 9 provided data missing data. Finally, 545 of the screened studies fulfilled our broad criteria and were included

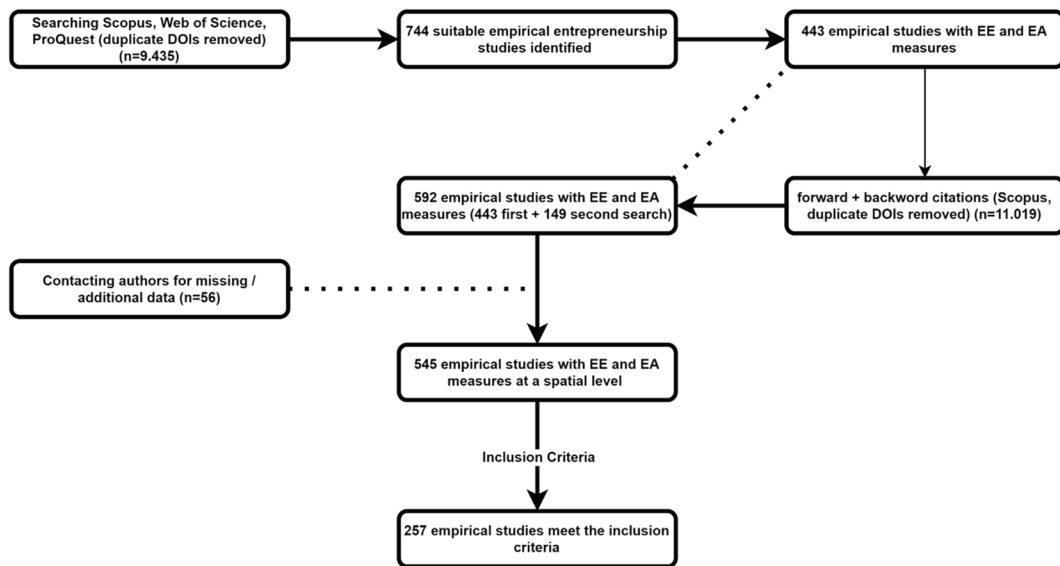


Fig. 1 Prism chart. Source: own illustration

in the initial dataset. To narrow the research scope and remain consistent with the conceptual boundaries of EEs described above, we then selected only the studies that were focused on a regional level. This ensured that our EE unit of observation represented the EE construct used in this meta-analysis. Our choice of observational unit originates from the EE studies by Stam (2015, 2018), Stam and van de Ven (2021), and Leendertse et al. (2022). This selection was operationalized by including only studies that took place at a lower administrative unit level. In EU countries, for instance, this would refer to the NUTS 2 level and lower levels. In other countries, equivalent filtering was done based on the territorial grids (e.g., TL3) published by the OECD.

The final dataset used in the meta-analysis contained 257 studies (see Supplementary Material G for a list of the included studies). Some of these studies contained information that could be extracted for specific separate time periods (e.g., 2000 and 2010), different countries (e.g., USA, UK, and Germany), or multiple dependent variables (e.g., new firm formation and total early-stage entrepreneurial activity). Data extraction thus yielded a total of 431 EA data points (K) (257 initial studies plus 28 for multiple country/time information plus 146 for multiple EA measures), covering a total of 2,241,813 space–time observations (N). The 431 unique EA data points

were matched to 4293 independent variables to identify the EE elements that serve as meaningful antecedents of EA.

We used the Pearson product–moment correlation—a measure of the direct relationships between two variables commonly used in systematic literature reviews—as the effect size indicator (Aguinis et al., 2011). In this study, one of the variables is a measure of EA (our dependent variable) and the other is a variable attributable to Stam’s EE framework (our independent variable). Any missing correlation coefficients from the studies were calculated in a two-step procedure. First, Cohen’s d was calculated based on the mean difference divided by the product of the standard deviations; second, the relationship between Cohen’s d and correlation coefficients was calculated. To prevent biases, the second step uses the sample size correction based on Hedges’ g (Borenstein et al., 2009).

3.2 Variable coding

A challenging aspect of this process was the categorization of the numerous extracted variables to the constructs used in the meta-analysis (Lipsey & Wilson, 2001). To accomplish this task, we applied systematic step-by-step grouping similar to Martin et al. (2013). Grouping the antecedents of EA (our independent

variables) based on the EE elements can be challenging as current EE frameworks do not provide clear definitions for the elements or identify the measurements that could belong to them, so there may be overlap or matching among elements. Our grouping process strictly adhered to the following procedure: First, all variable names, definitions, and sources were unified. Second, similar variables were grouped based on their sources, definitions, and objects of measurement (resulting in 132 categories). Third, the variables within each category were checked with respect to transformations from the primary study to harmonize the positive and negative directions within a category. Correlation signs were only switched if the authors in the original study explicitly outlined such transformations (e.g., inverted variables). Since the aim of this meta-analysis is to identify meaningful antecedents, we used as much unprocessed data as possible. Finally, the created categories were assigned to the elements in the Stam framework.

Within the final dataset, 25% of all variables were close to or the same as variables used by Stam (2015, 2018), Stam and van de Ven (2021), and Leendertse et al. (2022), making it easy to assign them to the framework elements. The remaining categories were coded via theory-based rationales for each EE element (Stam, 2015, 2018; Leendertse et al., 2022; Stam & van de Ven, 2021; Spigel, 2017). A necessary condition for each assignment was that it coincided with the categories' basic rationale for the EE elements (see Appendix 1, Table 4 and Supplementary Material G). For example, measures of human capital were grouped into the talent element based on the argument that skilled workers are a key part of the talent element of an EE (Leendertse et al., 2022; Stam, 2015). Classification of each category was performed by two of the authors separately. Disagreements were resolved by discussion until a full consensus was reached (Martin et al., 2013). The reliability of independent variable encoding was checked by comparing the groupings of the preliminary results with those of the final coding 5 months later, which resulted in an intertemporal reliability of 82%. We removed variables from the initial dataset due to limited prevalence or missing variable descriptions. The increase in content validity evidence brought by this sequential procedure helped to avoid the construct identity fallacy described by Steel et al. (2021).

Each extracted EA measure is either a general or productive EA measure. In the EE literature,

productive EA refers to entrepreneurship that particularly contributes to the output of the economy (Baumol, 1990). It is commonly measured in terms of knowledge-intensive firms, innovative new firms, or high-growth firms. Productive EA measures are associated with increases in regional development through employment and production growth (Acs, 2011; Fritsch & Schroeter, 2011). Both general and productive EA measures are used in combination in the total set, while the measures are used separately in a subgroup analysis. The productive EA measures contain variables such as the number of gazelle companies (Zhang & Roelfsema, 2020) or the number of knowledge-intensive start-ups (Fritsch & Schilder, 2008). The general EA measures include new firm formation, self-employment rates, and TEA. While each variable that measured productive EA was a measure of only productive EA, measures of general EA could also include aspects of productive EA. The other study-related characteristics extracted included publication type, research method, peer-review status, journal impact factor, time span, responses, imputation, and whether the study included an ecosystem variable in its model. A list of the countries covered by the identified empirical papers is provided in Supplementary Material A. These vast sets of moderators help explain the heterogeneity across these studies (Borenstein et al., 2009).

3.3 Analytical approach

The large, heterogeneous body of empirical studies required the use of random-effects-based meta-analytical models for data analysis and interpretation. A random-effects model is preferable because it accounts for heterogeneity within and between studies (Borenstein et al., 2009). We tested for heterogeneity among studies using Cochran's Q test for heterogeneity, the H test statistic, and I^2 (Cooper et al., 2019). The weights of the random-effects meta-analysis were constructed using the common inverse variance weighting method (Borenstein et al., 2009). To estimate the summary effect sizes, we relied on the Fisher z -transformation to accommodate skewed distributions of the correlation coefficient. To ensure that our results were relatively conservative, we relied on the Sidik–Jonkman estimator with a Knapp–Hartung adjustment. As noted by Jackson et al. (2017), this method performs well. Moreover, if a meta-analysis

is complemented by a sensitivity analysis and robustness checks, it leads to conservative results.

We took care in our research strategy to address threats to inference, such as sample or selection bias, publication bias, and the method-related biases mentioned by Cooper et al. (2019). Selection bias was addressed through our broad search strategy. We queried disparate search databases and applied a variety of search strings, exhaustive screening, and forward and backward citation searches to cover a large research area. We also did not have any inclusion restrictions regarding publication type. This created a large sample size that effectively covered the empirical literature and reduced systemic errors, indicating the absence of a potential selection bias.

Sample bias and its impact on effect size estimations were a larger source of potential concern. We accounted for this potential bias through reliability correction and harmonization of the effect sizes within the empirical studies. We calculated the mean correlation coefficients of the independent variables belonging to a single framework element (K) per study. This helped us avoid sampling errors and oversized study weights. The impact of between-study weights was addressed through a variety of weighting techniques (fixed effect, mean, median, space–time N , and reported N). We also identified duplicate correlation coefficients within the final dataset to avoid oversampling. Finally, we accounted for data source homogeneity with meta-analysis regression analysis (MARA).

Potential problems emerging from the meta-analysis itself were evaluated through model design changes and MARA. The design changes consisted of the use of different subsets and aggregation levels (e.g., reported study observation in comparison to space–time observations) as well as modified study weighting schemes (e.g., mean, median, fixed effects). MARA was used to incorporate sets of moderators and hyperparameters to validate findings from the general random effects model. MARA is not used as the main method for analysis due to two main considerations. First, according to Oxman and Guyatt (1992) and Schmidt (2017), MARA produces unreliable results in cases of very large between-study heterogeneity, ex post selection of moderators, non-normal data, and large subgroups. The second argument relates to the model itself and how it is estimated. To estimate categorical moderators and to avoid perfect multicollinearity, MARA has to omit one reference

category from each set of mutually unique and jointly exhaustive variables (similar to Gechert & Rannenberg, 2018). This choice might lead to an arbitrary selection of reference categories, which could affect the results and subsequent interpretation.

Our MARA procedure aligned with Borenstein et al. (2009), Cheung (2019), and Steel et al. (2021), addressing the unit-of-analysis error and allowing us to evaluate the behavior of the effect size estimate in the presence of study-specific characteristics. Because of the large number of both collected studies and entries per study, we expanded the regular MARA to a three-layer MARA. In cases where the individual effect sizes are assumed not to be independent, as in our study, a three-layer MARA is recommended by Cheung (2019). In general, our procedure can be summarized as two stacked random-effects models, where we assume a normal distribution of estimated effect sizes. The three-level model for this meta-analysis followed three pooling steps. The first pooling of effect sizes was on the study-aggregate level to account for the different EA measures in each study and their interdependence. The second pooling cluster was at the study level, represented by a unique study identifier, to accommodate primary variable selection and its dependence on the used EA measure. In the last layer, we estimated the overall true effect size (similar to the single random effects model). Following Harrer et al. (2021), all the estimations and calculations were performed using the statistical software R.

4 Results

4.1 Meta-analytical results

The results of the meta-analysis of the direct relationships between EE elements and EA are reported in Table 1, which shows the results for each of the ten framework elements in the overall sample. Table 2 differentiates the results by the dependent variables. As the element of leadership was included in fewer than five studies in the productive EA subset, it is excluded from this subset.

As can be seen in Tables 1 and 2, the meta-analysis yielded non-significant results across all subsets considered for the EE elements *networks* and *physical infrastructure*. The *networks* element consists

Table 1 Results for the total sample

Set	Independent variable	K	N	$\hat{\tau}$	$\hat{\tau}_{SD}$	Z score	p value	95% CI	
								Lower limit	Upper limit
Total sample	Networks	93	283,318	-0.04	0.10	-0.41	0.68	-0.24	0.16
	Leadership	17	15,321	0.34	0.08	4.49	0.00	0.20	0.47
	Finance	85	332,008	0.21	0.06	3.30	0.00	0.09	0.32
	Talent	404	1,022,974	0.16	0.03	6.00	0.00	0.11	0.21
	Knowledge	184	326,424	0.05	0.04	1.50	0.13	-0.02	0.12
	Support services/intermediaries	78	125,835	0.13	0.08	1.68	0.09	-0.02	0.27
	Formal institutions	90	256,984	0.36	0.10	3.96	0.00	0.19	0.51
	Culture	168	565,731	0.14	0.05	2.65	0.01	0.04	0.24
	Physical infrastructure	101	205,382	0.08	0.07	1.23	0.22	-0.05	0.22
	Demand	384	991,298	0.23	0.03	8.26	0.00	0.17	0.28

$\hat{\tau}$ estimated population effect size, with a random effects model; $\hat{\tau}_{SD}$ is the standard deviation of estimated population effect size; K number of studies, N total sample size, CI confidence interval

Table 2 Results for productive and general entrepreneurial activity

Set	Independent variable	k	N	$\hat{\tau}$	$\hat{\tau}_{SD}$	Z score	p value	95% CI	
								Lower limit	Upper limit
General entrepreneurial activity	Networks	75	248,895	-0.07	0.12	-0.56	0.57	-0.30	0.17
	Leadership	14	12,450	0.32	0.06	5.18	0.00	0.20	0.43
	Finance	65	311,762	0.17	0.08	2.15	0.03	0.02	0.32
	Talent	302	873,100	0.16	0.03	5.02	0.00	0.10	0.22
	Knowledge	120	218,850	-0.01	0.05	-0.17	0.86	-0.11	0.09
	Support services/intermediaries	56	99,902	0.02	0.09	0.19	0.85	-0.15	0.18
	Formal institutions	78	243,326	0.35	0.10	3.59	0.00	0.17	0.52
	Culture	142	518,556	0.11	0.06	1.74	0.08	-0.01	0.22
	Physical infrastructure	79	179,867	0.09	0.08	1.02	0.31	-0.08	0.24
	Demand	294	875,871	0.21	0.03	6.26	0.00	0.15	0.27
Productive entrepreneurial activity	Networks	18	34,423	0.08	0.12	0.65	0.51	-0.16	0.31
	Leadership	-	-	-	-	-	-	-	-
	Finance	20	20,246	0.33	0.07	4.79	0.00	0.20	0.45
	Talent	102	149,874	0.16	0.05	3.31	0.00	0.07	0.26
	Knowledge	64	107,574	0.17	0.03	4.90	0.00	0.10	0.23
	Support services/intermediaries	22	25,933	0.39	0.14	2.85	0.00	0.13	0.60
	Formal institutions	12	13,658	0.42	0.28	1.62	0.11	-0.09	0.76
	Culture	26	47,175	0.33	0.09	3.76	0.00	0.16	0.48
	Physical infrastructure	22	25,515	0.08	0.10	0.82	0.41	-0.11	0.27
	Demand	90	115,427	0.28	0.04	6.92	0.00	0.20	0.35

$\hat{\tau}$ estimated population effect size, with a random effects model; $\hat{\tau}_{SD}$ is the standard deviation of estimated population effect size; k subset of all the studies (K); N total sample size; CI confidence interval

of empirical proxy measures such as firm/business density and private connectedness, while the *physical infrastructure* element includes empirical proxy

measures such as internet penetration rate, a metropolitan city dummy, and transportation infrastructure (see Supplementary Material F).

Three EE elements showed statistically significant results across all subsets, with consistent positive effects on EA. For the first element, *finance*, the estimated statistically significant effect size slightly diverges across the subsets. The estimated small effect size in the general EA subset and moderate effect size on the productive EA subset combine to an overall small effect size (due to the share of studies the two subsets have in the overall sample). *Finance* consists of empirical measures such as VC capital within the region, access to capital, and ease of getting credit (see Supplementary Material F). The element of *talent*, which also shows a persistent small statistically significant positive effect, relies on empirical measures such as secondary and tertiary education and employment indicators (see Supplementary Material F). *Demand* relies on empirical measures such as population (e.g., total, growth), GDP per capita, and GDP derivatives (see Supplementary Material F).

In addition to these three EE elements of *finance*, *talent*, and *demand*, the EE element of *leadership* also has a consistently significant positive effect in the examined subsets. However, we were unable to examine this element in the context of productive EA, as there was not sufficient data for a robust estimation. The estimated statistically significant effect sizes for the *leadership* element in the two subsets we could examine exhibit a medium or moderate-sized relationship as an antecedent of EA. The *leadership* element includes variables like innovative project leaders, the share of high-growth firms, and perceptions of leadership, as well as leadership behavior in the population (see Supplementary Material F). Finally, the EE element of *culture* shows statistically significant positive effects across all subsets, though only marginally significant for the general EA subset. The effect size of *culture* is small for total and general EA, but moderate for productive EA. *Culture* relies on empirical measures such as culture proxies (e.g., religion, democracy, social norms), cultural indices (e.g., uncertainty avoidance), and historic EA (see Supplementary Material F).

For the remaining EE elements, the meta-analysis yielded inconsistent evidence. The results for the EE element *knowledge* show a small statistically significant positive effect size for productive EA only. The estimates for total EA and the general EA subsets do not statistically differ from zero. The empirical measurements of patents, R&D spending, and universities are aggregated to the *knowledge* element (see

Supplementary Material F). The EE element *support services/intermediaries* shows a moderate statistically significant effect size for productive EA, which becomes a small statistically significant effect size for overall EA and is not statistically significant for general EA. The *support services/intermediaries* element relies on empirical measures such as the ease of doing business, incubators, and government entrepreneurship support programs (see Supplementary Material F). Finally, the estimated effect size for the *formal institutions* EE element was moderate for total and general EA but was statistically insignificant in the productive EA subset. The *formal institutions* element consists of variables such as government-related indicators (e.g., government employment, consumption, governance), rule of law, and taxes (see Supplementary Material F).

4.2 Focusing on the systemic dimension of EEs

The meta-analytical synthesis helped to understand the antecedents of EA through the lens of the EE framework by identifying the significant individual EE elements. The meta-analytical synthesis, however, cannot provide conclusive evidence for the systemic nature of EEs. Nevertheless, the coefficients of determination reported in the sampled empirical studies (i.e., R^2) offer a proxy for capturing this systemic nature. The reported coefficient of determination can be seen as a measure of how well the independent variables (i.e., the EE elements) explain EA. In this context, an empirical study with independent variables that cover multiple EE elements (e.g., Demand, Talent, Knowledge, Formal institutions) is hypothesized to have a higher coefficient of determination in contrast to a study that only covers a single EE element (e.g., Demand only). The studies that cover more EE elements through their various diverse set of independent variables are better suited to explain EA, hence partially accounting for the interdependencies. In this vein, a study that covers more EE elements would cover a greater share of systeminess of EEs and, therefore, explain better EA than studies with fewer elements. Figure 2 plots the R^2 and the number of elements covered by each study. The results confirm that the coefficient of determination increases when more unique different spatial endowments (demand, finance, talent, culture, knowledge, support services), i.e., EE elements, are present in the empirical study. This implies that studies which cover multiple EE elements

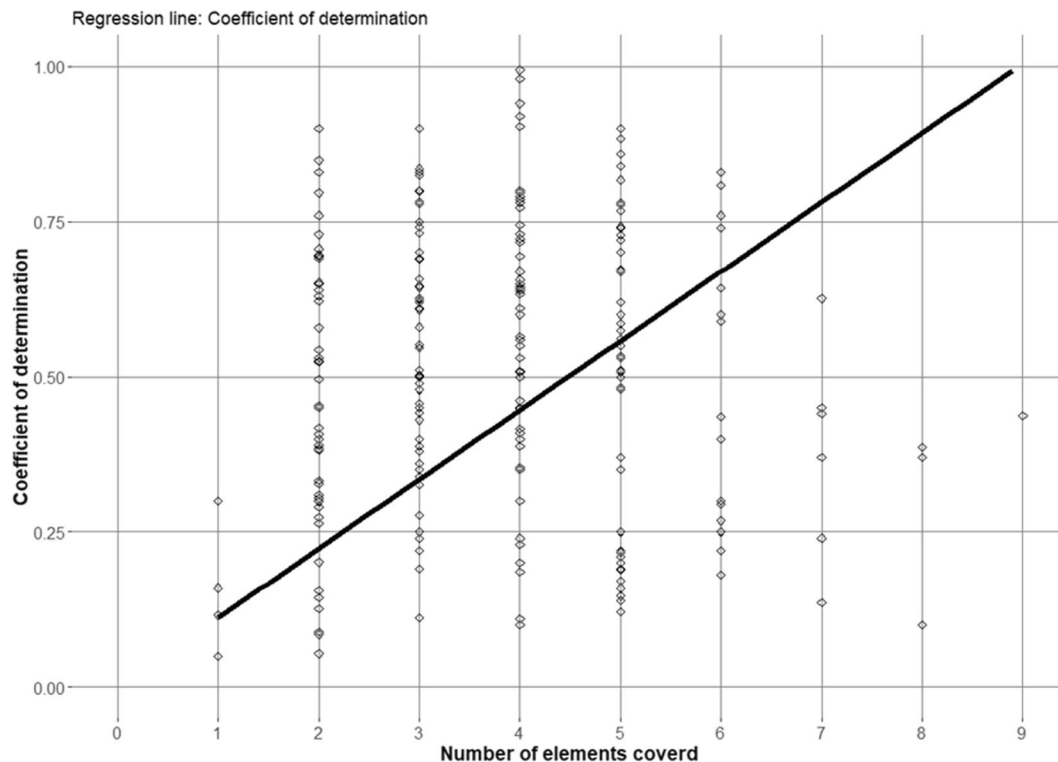


Fig. 2 Number of elements covered and R^2 reported in studies included in the meta-analysis. Note: The regression line is obtained through an ordinary least squares regression without an intercept. The intercept is omitted since a study with no coverage of elements is omitted in this meta-analysis and hence a study with no variables can have a common explana-

tory power to explain the variation of EA. To accommodate for this drawback, we performed robustness regressions for subsets (e.g., research method, EA type and cluster) and checks with respect to the number of variables used in these original studies

(and potentially their interdependencies) have higher explanatory power and better explain (foster) EA. This result remains robust when controlled for study characteristics (e.g., account for number of independent variables and research designs).

4.3 Robustness checks

4.3.1 Robustness of the methods

We first validated our choice of methods by applying different aggregation and weighting methods to confirm the results of the standard random effects model. The applied fixed-effects model failed to yield the same results (see Supplementary Material B), but this can be explained by differing between-study weights. Robustness checks indicated that when the number of studies per framework and subset was small, the

results diverged from the random-effects model. The unweighted measures can be seen as a lower bound of the effect size estimate. These estimates largely confirmed our results. The random-effects model, which uses total observations as between-study weights, exhibited only minor differences from our reported results (see Supplementary Material C). The three-layer MARA, which accounted for dependent effect size measures, also confirmed these findings (see Supplementary Material D), indicating that our results remain consistent across different models and weighting methods.

4.3.2 Publication bias

A major source of concern in a meta-analysis is potential publication bias. We followed recommendations from Steel et al. (2021) and used Egger's regression,

the trim-and-fill technique, Rücker's limit meta-analysis method, and *p*-curve analysis to detect the potential presence of publication bias. The results of Egger's test show the absence of funnel plot asymmetry for all EE elements, which accordingly suggests the absence of publication bias, except for the *physical infrastructure* element. However, the trim-and-fill results for *physical infrastructure*, as well as Rücker's limit meta-analysis results, show the reliability of the estimate for this element. Given the extreme heterogeneity of the studies, we adopted a second strategy, following Cooper et al. (2019), and tested for publication bias with a three-layer MARA (see Supplementary Material D). Because of the screening process we employed, a variety of types of empirical research were included in this meta-analysis. To control for publication characteristics, we used measures of publication type (e.g., paper, book, dissertation) and publication quality (e.g., impact factor, peer-reviewed status, inclusion of EA measures as the dependent variable) as proxies for publication bias. For each framework element, a three-layer MARA was estimated with these publication-related controls to detect publication bias. Across all settings, the estimates for the variables of publication type, impact factor, and peer-reviewed status were not significant, indicating the absence of publication-related bias and aligning with our previous findings. Overall, these additional analyses indicated that the random effects model results show robust effect size estimates for all framework elements.

4.3.3 Robustness of variable coding and grouping

We also evaluated the robustness of the coding and the corresponding constructs using random-effect models and three-layer MARA. The first check was based on the empirical variables used in the previous studies by Stam (2015, 2018), Stam and van de Ven (2021), and Leendertse et al. (2022) (see Supplementary Material E). In general, our results were similar to those previously reported if the numbers of variables and observations were sufficiently large. The results regarding the *demand*, *finance*, *support services*, *physical infrastructure*, and *talent* elements were similar with respect to effect size, direction, and significance, but the results for the other elements differ.

The second robustness check focused on the categories and pooling of effect sizes at the paper level

by framework element. To evaluate how this pooling influenced the final effect size estimates, a two-stage random-effects model was calculated. In the first stage, we estimated a random-effects model per category, and in the second stage, we estimated the element-wise random-effects model. In the second stage, the input was the estimated effect size and standard deviation of the first random-effects model. The results for the *demand*, *finance*, *formal institutions*, *networks*, *physical infrastructure*, and *talent* elements are consistent. For the elements of *culture*, *knowledge*, and *support services*, the new results yielded higher effect size estimates than those reported in the previous section.

The next evaluation focused on the grouping process and how the directions of correlation coefficients impact the effect size estimates. This procedure helped account for the ambiguity of the empirical operationalized variables used in the studies. We used a two-stage random-effects model consisting of absolute correlation coefficients based on the 132 categories developed in our coding procedure. In the first stage, the effect size and standard deviation of each category were estimated. In the second stage, another random-effects model for each of the ten EE framework elements was used, with the estimated effect size and standard deviation from the first stage as inputs. The absolute deviation of the effect sizes was used to investigate framework element relevance and significance. These results are reported in Table 3 and show that across all settings, all framework elements are meaningful antecedents of EA. These results support the reliability and validity of our reported results and the relevance of the EE framework in general.

Our final check focused on the encoding and assignment of variables to categories and, ultimately, to the framework elements. A three-layer MARA was employed with a binary variable to test whether the variables in a given element have a similar effect size compared to those studies with an EE measure (see Supplementary Material D). For the framework elements of *culture* and *finance*, the estimated effect sizes underestimate the potential true effect size for the respective elements (i.e., the binary indicator is statistically significant). For all other elements, there is no difference between EE measures and the variables assigned to the framework elements, underlining the validity of our grouping procedure.

Table 3 Robustness check for correlation aggregation

Set	Independent variable	<i>K</i>	<i>N</i>	$\hat{\rho}$	$\hat{\rho}_{SD}$	<i>Z</i> score	<i>p</i> value	95% CI	
								Lower limit	Upper limit
Total sample	Networks	93	283,318	0.06	0.05	1.15	0.25	−0.04	0.17
	Leadership	17	15,321	0.34	0.07	4.85	0.00	0.20	0.48
	Finance	85	332,008	0.37	0.08	4.51	0.00	0.21	0.52
	Talent	404	1,022,974	0.23	0.04	5.04	0.00	0.14	0.31
	Knowledge	184	326,424	0.20	0.05	3.62	0.00	0.09	0.30
	Support services/intermediaries	78	125,835	0.16	0.05	3.54	0.00	0.07	0.25
	Formal institutions	90	256,984	0.19	0.05	3.75	0.00	0.09	0.29
	Culture	168	565,731	0.24	0.06	3.84	0.00	0.12	0.36
	Physical infrastructure	101	205,382	0.21	0.08	2.45	0.01	0.04	0.37
	Demand	384	991,298	0.24	0.04	6.17	0.00	0.16	0.31
General entrepreneurial activity	Networks	75	248,895	0.06	0.05	1.17	0.24	−0.04	0.17
	Leadership	14	12,450	0.29	0.05	6.05	0.00	0.20	0.39
	Finance	65	311,762	0.35	0.09	3.81	0.00	0.17	0.53
	Talent	302	873,100	0.23	0.05	5.06	0.00	0.14	0.32
	Knowledge	120	218,850	0.28	0.06	4.50	0.00	0.16	0.41
	Support services/intermediaries	56	99,902	0.17	0.02	7.65	0.00	0.13	0.21
	Formal institutions	78	243,326	0.20	0.05	3.81	0.00	0.10	0.30
	Culture	142	518,556	0.26	0.07	3.78	0.00	0.12	0.39
	Physical infrastructure	79	179,867	0.23	0.08	2.75	0.01	0.07	0.39
	Demand	294	875,871	0.24	0.04	5.81	0.00	0.16	0.32
Productive entrepreneurial activity	Networks	18	34,423	0.09	0.05	1.97	0.05	0.00	0.18
	Leadership	-	-	-	-	-	-	-	-
	Finance	20	20,246	0.21	0.07	2.92	0.00	0.07	0.35
	Talent	102	149,874	0.26	0.06	4.26	0.00	0.14	0.38
	Knowledge	64	107,574	0.22	0.07	3.02	0.00	0.08	0.36
	Support services/intermediaries	22	25,933	0.19	0.11	1.65	0.09	−0.04	0.41
	Formal institutions	12	13,658	0.20	0.07	2.83	0.00	0.06	0.34
	Culture	26	47,175	0.29	0.09	3.08	0.00	0.11	0.47
	Physical infrastructure	22	25,515	0.22	0.06	3.83	0.00	0.11	0.34
	Demand	90	115,427	0.24	0.05	4.86	0.00	0.14	0.34

$\hat{\rho}$ estimated population effect size, with a random effects model; $\hat{\rho}_{SD}$ is the standard deviation of estimated population effect size; *K* number of studies; *N* total sample size; *CI* confidence interval

5 Discussion

5.1 Summary and implications

This meta-analysis was motivated by the goal of providing a basis for a shift in the EE literature toward a coherent EE theory. Our comprehensive meta-analytical synthesis provides a foundation for shifting the EE literature from an EE concept toward an EE theory and

reveals the significance of multiple individual EE elements, not only for our total sample but also for several subsets, such as the type of EA measured. The results show significant positive relationships between many EE elements and EA, which is in line with the broader body of literature on EE elements but some findings are contrary in part to the existing EE literature, which highlights the importance of most or all EE elements, both from conceptual perspectives (Spigel, 2017; Wurth

et al., 2021) and in empirical contributions (Stam & van de Ven, 2021; Leendertse et al., 2022). An overview of the significant elements is provided in Fig. 3.

Confirming the relevance of the elements with findings from hundreds of studies across different continents empirically underpins the strength of EEs for explaining EA. In addition to some variations in the results, the elements of *networks* and *physical infrastructure* remain non-significant for most subsets and models. The relevance of *networks*, while well researched at the individual level, is not empirically clear in EE research at the regional level (Stam & van de Ven, 2021; Leendertse et al., 2022). It is important to note that some research in the field highlights the importance of networks for the other EE elements. Networks are ties (e.g., homophilic ties & heterophilic ties) of individuals to other individuals or agents that act as connectors to access or provide beneficial EA-enabling resources, which is why networks can be seen as a cohesive or connecting mechanism rather than an

individual element (Komlósi et al., 2022; Prokop & Thompson, 2023). Our findings did not show a significant relationship between *networks* and EA. Delving deeper into the data shows that neither individual measures of *networks*, such as social capital or network ties, nor firm-level measures, such as business density, show significant relationships with EA. A potential reason for these results is that the existing measures used by the literature for the abstract phenomena networks might be inadequate measures to capture the complexity of the EE element networks. The existing measures are rather artifacts or proxies for related EE elements. For instance, aggregated social network measures might better explain the regional cultural element (Fritsch & Wyrwich, 2023) than the enabling factor of networks between individuals to have easier access to talent, finance, knowledge, and support services.

The non-significance of *physical infrastructure* could be due to the different timespans and geographies of the studies included. Future research could deeply analyze

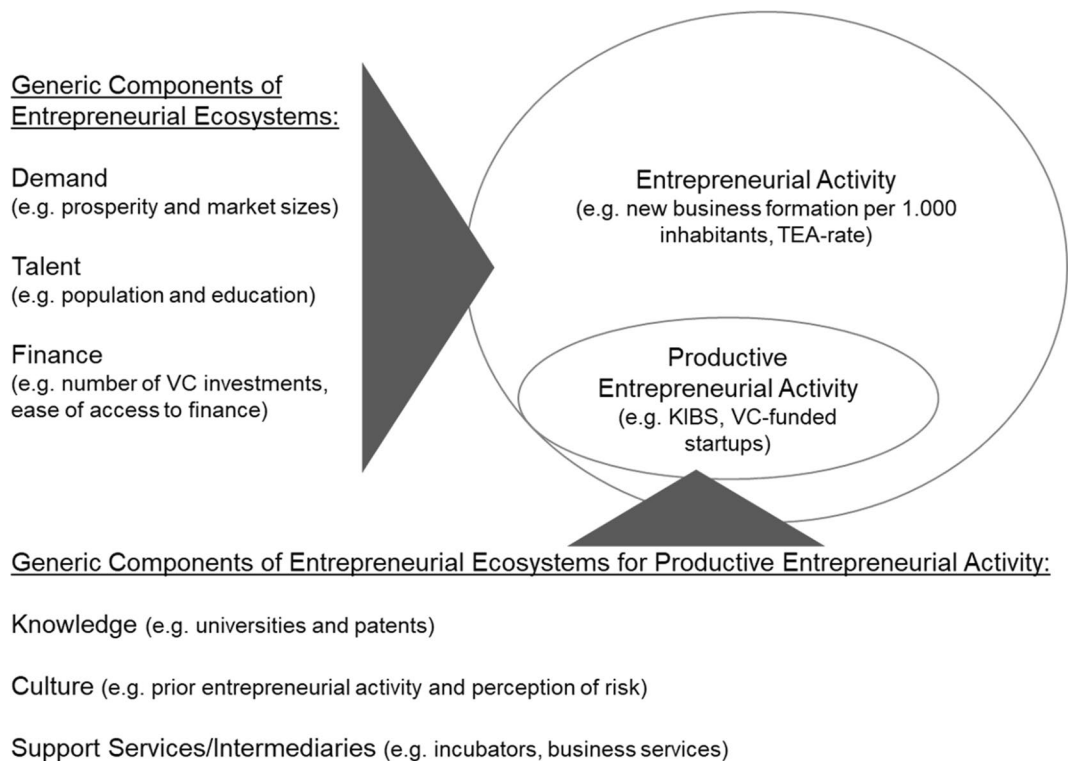


Fig. 3 Generic components of entrepreneurial ecosystems. Source: own illustration. TEA total early-stage entrepreneurial activity. KIBS knowledge-intensive business start-ups. VC

venture capital. Components derived from meta-analysis of 257 quantitative studies on the antecedents of regional-level entrepreneurial activity across the globe

whether the role of infrastructure has changed over time. It is possible that physical infrastructure in some countries plays a different role today compared to 20 or 30 years ago, i.e., after a “critical mass” of infrastructure was achieved or general infrastructure was sufficiently developed. Morretta et al. (2020), for instance, point out that the lack of sufficient infrastructure hampers regional EA because entrepreneurs cannot fully utilize regional endowments. Additionally, underdeveloped infrastructure limits efficient allocations of regional resources and interferes with or constrains economic activity (Castelnovo et al., 2020; Morretta, 2021). Building a necessary level of infrastructure is sufficient to promote entrepreneurship, economic activity, and regional growth (Castelnovo et al., 2020; Chaurey & Le, 2022; Morretta, 2021; Morretta et al., 2020). However, Crescenzi and Rodríguez-Pose (2012) conclude that when a minimum level of infrastructure development has been achieved the returns on new infrastructure decline. The meta-analysis results are consistent with this argumentation for traditional measures of infrastructure (electricity, road, train network, etc.). They showed no significant effect on EA, potentially because many of the empirical studies are from developed countries with a sufficiently developed level of basic infrastructure. Only the ICT infrastructure measures show a statistically significant moderate effect size on EA. Even in developed countries the level of ICT infrastructure may not have reached a sufficient level of development yet (ITU, 2023; OECD, 2020), which is why it may constrain EA and ICT infrastructure development still results in additional EA.

Our dataset also reveals some important gaps in research regarding EE elements. As reported in the results tables, the element of leadership was covered by the fewest studies (17) but showed a statistically significant moderate effect size. Authors researching particular EE cases highlight the role of entrepreneurial leaders and role models in EEs (Motoyama & Knowlton, 2017; Spigel, 2017); however, many empirical studies, even if specifically aimed at analyzing EEs, omit them (Abootorabi et al., 2021; Audretsch & Belitski, 2021; Content et al., 2020). Leadership may be strongly related to other EE elements (e.g., talent and culture), therefore be an essential element of an EE but because of the lack of sufficient empirical evidence, this meta-analysis is not able to draw generalizable (definitive) conclusions. More research on this element is needed, as role models are important drivers of EA (Bosma et al., 2012) but remain under-researched in the EE context.

Our results also differentiate the types of entrepreneurship that are related to EE elements. Findings differ when comparing the type of entrepreneurship measured in the extant papers (i.e., general EA vs. productive EA). Our results show that both types of EA have highly significant relationships with *finance*, *talent*, and *demand*. To a lesser extent, this also applies to the elements of *culture* and *formal institutions*, which are both significant for only one type of EA but only slightly below or above the 10% significance level for the other type. *Physical infrastructure* is non-significant for both types of EA, analogous to the finding in the total sample. However, key differences between types of EA exist for some EE elements. The elements of *knowledge* and *support services/intermediaries* only show a significant relationship with productive EA. The estimation procedure covered a wide range of *knowledge* proxies (e.g., patents, R&D expenditure, universities; see Supplementary Material F) but remained ambiguous. The results indicate that *knowledge* is more relevant for innovative or productive EA than for other types of EA. Knowledge-based capital and knowledge-intensive entrepreneurship (e.g., high-tech venture vs new small retailer), for instance, are key factors for productive EA with associated impacts (e.g., economic growth, employment growth; Amoroso & Link, 2018; Radosevic & Yoruk, 2013). These general findings for the *knowledge* and *support services/intermediaries* elements open fruitful avenues for further research on the interactions between both types of EA and whether some regions establish EEs with strong elements that support one type before later also support the other type of EA.

5.2 Shift toward an EE theory

Our findings provide a starting point for formulating a basic EE. The results of the meta-analysis show that not all EE elements are significantly related to total EA. After dividing the total sample set into subsets focusing on different types of EA and performing several robustness checks, we find that the elements that show significant relationships with EA differ strongly from each other. As shown in Tables 1 and 2, the elements of *demand*, *finance*, and *talent* have a persistent moderate statistically significant effect size. The leadership element is omitted due to the limited number of empirical studies and hence lack of generalizability.

The remaining elements have varying statistical significance, suggesting they are not fundamental elements of any EE. Hence, we posit the following proposition for a theory on EEs:

Proposition I: *To facilitate EA, an EE needs to have generic components such as demand (market size, economic growth), finance (availability and accessibility of venture capital), and talent (growth of the workforce, education of the population).*

Generic components refer to components that must be present in any type of EE to foster EA. How these components are formed or designed is irrelevant to an EE's effect on EA. For example, the presence of demand could be achieved not only through an existing, developed market but also through a growing market that offers opportunities for the individual entrepreneur. This first proposition asserts that the design of any EE requires generic "core" components: markets with demand and supply (demand element), availability of financial or risk capital for entering markets (finance element), and human capital (talent element). These generic components are the basic endowments essential to foster any form of EA.

In addition to these three identified generic components, the elements of *culture* and *formal institutions* have statistically significant effect sizes for the total, or overall, EA (Table 1) but their significance varies with regard to the type of EA. The general role of formal institutions with, for instance, property rights and tax laws is shaping the entire economic activity landscape rather than just the individual EA component of economic activity (Haggard et al., 2008; Rutherford, 2001). The general results (Table 1) confirm the importance of formal institutions but when zoomed in to the EA types the general framework of economic activity becomes less relevant for productive EA. Although culture and formal institutions are relevant for EA their specific importance and variation must be addressed when further developing EE theory. This differentiation suggests that productive EA is different in nature from general measures of EA, i.e., it is also significantly related to knowledge, culture, and support services/intermediaries. Table 2 shows that these elements have a statistically significant positive effect size, indicating their necessity for that specific type of EA. Hence, we posit the following proposition:

Proposition II: *All types of EA are facilitated by the generic components of EEs. To foster productive entrepreneurship activity, the additional components of knowledge (presence and output of research facilities), culture (prior rates of EA and risk perception), and support services (facilities and organizations enhancing start-up procedures) need to be present.*

Proposition II implies that an EE with the specific goal of generating productive or innovative EA requires the additional components of entrepreneurship culture (i.e., how a society perceives entrepreneurship and how persistent it is rooted in the society; culture element) (Fritsch & Wyrwich, 2019; Fritsch et al., 2019), agents that help the individual entrepreneur or firm thrive (support services element), and knowledge capital (technology push; knowledge element). These components are relevant antecedents of productive EA. While the generic components are required for baseline EA, the specific elements of *knowledge*, *culture*, and *support services* increase the likelihood of the emergence of productive or innovative EA.

From a theoretical perspective, the foundation for these generic components is analogous to Camagni's (2008) theory of territorial capital regarding regional economic growth. In this theory, tangible and intangible regional endowments are utilized for production, obtaining a more efficient allocation of assets to generate innovation, and building regional comparative advantages (Camagni, 2008; Castelnovo et al., 2020; Morretta et al., 2020). Our findings particularly support the importance of intangible endowments (such as talent), i.e., the generic components of EEs. When these endowments are sufficiently available, starting any type of firm is easier, and more EA occurs (Proposition I). It is important to highlight that an EE theory, like territorial capital (Morretta, 2021), must integrate the endogenous and exogenous forces that produce EA and account for the combination of both forces. The introduction of generic components allows us to model first-level core causal relationships (in light of Corley & Gioia, 2011) about the general phenomenon (Proposition I). Proposition II, in turn, describes how a shift in EA output type (general to productive) could potentially be achieved when available resources are accumulated, enhanced, mobilized, and integrated (similar to territorial capital; see Morretta, 2021). This shift will lead to new innovative firms and change the composition of EA within the region.

Combining both propositions (Fig. 3) therefore provides a foundation for the development of a comprehensive EE theory that explains the conditions under which EA takes place. Conceptual contributions on EEs suggest that EEs differ and that variations among EEs can be explained by the EE frameworks' specifics and coherence (Brown & Mason, 2017; Roundy et al., 2017). Accordingly, and in light of Fig. 2, we propose the following regarding the form and circumstances in which these components are embedded:

Proposition III: *The form of the generic components needed in an EE depends on the region in which the EE is located. The quantity and quality of elements present influences the primary output of the EE, which is EA.*

5.3 Future research

The meta-analytical findings, their theoretical implications, and our comprehensive dataset facilitate important next steps for future research. We call for the further development of the causal mechanisms of EEs' effects on EA, based on our initial propositions. Research should seek to determine whether the generic components we have derived are mutually dependent and, if so, how they influence each other. Moreover, our analysis shows that not all elements of an EE necessarily significantly relate to EA and this is likely to hold across all EE frameworks. To take this into account, as well as potential study-specific or location-specific peculiarities that might further affect the extent to which each EE element contributes to EA, future studies making use of an index reflecting the overall EE should conduct sensitivity analyses to determine the extent the results would differ if elements of the EE framework were abandoned or weighted differently. A sophisticated sensitivity analysis, such as that done by Autio et al. (2018), would provide more transparent and substantive information about the relevance of each EE element and facilitate judgment of the robustness of the EE scores to researchers' choices underlying the selection of EE elements and variables, respectively (Autio et al., 2018; Saisana et al., 2005).

Additionally, further research could extract correlations among the independent variables in prior studies and use structured equation modeling to further analyze latent underlying systemic variables. As

an example, future studies could empirically analyze the influence of general EA (as a proxy for the culture in a spatial area) on productive entrepreneurship and whether its impact is moderated by other EE elements. As prior entrepreneurship rates are known to influence present EA and are strongly related to entrepreneurial attitudes and regional entrepreneurship culture (Fritsch & Mueller, 2007; Fritsch & Wyrwich, 2019), further research should test our proposed Proposition II, questioning whether some EEs have stronger relationships to certain types of EA and why this may be the case. It is possible that EEs must complete a development phase that fosters one type of EA before progressing to a phase that fosters the other type.

Future research should also analyze the cross-level linkages between elements that we found to be relevant at the regional level and the structures that are relevant at the national level. There are open questions as to whether different regional EEs combine to national or supra-national EEs or whether the institutional context, as a national framework, shapes specific bridge elements, such as culture, which then manifest in regionally embedded elements, such as knowledge. EEs are likely nested in larger macro-economic structures, such as national innovation systems (Fagerberg & Srholec, 2008; Lundvall et al., 2002), that differ across countries and continents. The national level of entrepreneurial and innovation systems has been argued to be of high relevance, given that a large portion of policy and legislation is developed on this level (Lundvall et al., 2010). While conceptual work on the interplay between different levels of EEs exists (Fagerberg & Srholec, 2008; Lundvall et al., 2002), further empirical analysis of this spatial and contextual embeddedness is needed.

The spatial embeddedness of EEs appears similar to the innovation system concept of Lundvall (2007). Innovation and competence building rely on distinct micro, meso, and macro-level structures with interdependent relationships that can be influenced by policymakers and managers to endogenously stimulate the system (Haarhaus et al., 2020; Lehmann & Schenkenhofer, 2020; Lundvall, 2007). EE research faces the same challenge to develop a theoretical model of this spatial and contextual embeddedness, as well as identify how other systemic views (business and innovation ecosystems, spatial approaches) form a union, intersection, complementary difference, or symmetric difference to each other.

Furthermore, theory development and empirical research on the EE concept need to address how temporally persistent the elements are and how consistently they influence EA over the long run. Some EE elements such as human capital, regional/national governance, knowledge capital, entrepreneurship support, financial capital, and market supply/demand are bound to the external environment and have the potential to fluctuate to a greater extent. Other elements like entrepreneurial culture and physical infrastructure can be seen as more stable conditions. As shown by Fritsch et al. (2019) and Fritsch et al. (2022), the effect of regional culture, for instance, has a strong continual impact on EA. Historical events—such as the existence of a technical university 100 years ago, self-employment rates 100 years ago, or a gold rush mentality—often still shape the regional/spatial entrepreneurial culture today (Alegre & Berbegal-Mirabent, 2015; Fritsch & Wyrwich, 2023; Nasra & Dacin, 2010). Similarly, the cultural setting of a region influences the inclination of individuals to potentially become entrepreneurs (Fritsch et al., 2019; Obschonka et al., 2015, 2020). These interdependencies must be addressed in an inclusive EE framework.

In addition to these recommendations, our comprehensive literature search and meta-analytical dataset provide two further insights that future research may build on. First, among the 4293 independent variables we identified in the literature, the vast majority were taken from official national statistics and global indicators such as the World Bank's World Development Indicators, Doing Business, the World Governance Indicators, and similar sources. Considering the growing number of EE studies, we suggest that further research should analyze single databases and provide in-depth overviews of the evidence provided by such data sources to identify stylized facts (Rauch, 2020). Future research would also benefit from incorporating new types of data sources, such as big data or social media data (examples include Bloh et al., 2020; Johnson et al., 2022), which we rarely found in the studies we reviewed.

6 Limitations and concluding remarks

Our makes several theoretical and methodological contributions, as we have discussed. However, a few

potential limitations of the study must be addressed. The methodology we used to obtain our empirical results is somewhat novel, especially within the literature on EEs. Because the purpose of this meta-analysis was to provide a generalizable empirical foundation to facilitate the development of an EE theory, we had to primarily focus on aspects connected to the generalizability of EE elements across settings and specific regions. In so doing, the meta-analysis summarizes the unique settings of the studies into overarching empirical estimates and primarily relies on averages of the focal effects of interest. It must be noted that such a focus on averages has been criticized in the entrepreneurship literature, suggesting that it neglects to consider that entrepreneurship is driven by deviation and differences and it ignores the value and relevance of uniqueness (Baker & Welter, 2014, 2021).

The quality of a meta-analysis is limited by its input. As a limited range of data sources exists in the studies we found, research on the antecedents of EA suffers from common source bias, as do any meta-analyses building on it. Additionally, our findings are limited by the grouping process we used for the variables, which revealed some of the shortcomings of previous research on EEs. If one develops a theory on EEs and then empirically tests its elements, it becomes difficult to find suitable data for such tests (Credit et al., 2018). Despite the mentioned limitations, the grouping of variables based on EE elements is suitable for our research purpose, as it allows for a comprehensive synthesis of a large number of studies; however, it also bears risks as there might be subjectivity and imprecision leading to differences in coding. By applying intertemporal and intercoder reliability, we reduced the risk of invalid grouping as much as possible. Nevertheless, other frameworks or different approaches to grouping could be adopted in future research.

Hence, our study should be viewed as the first step in a journey towards an EE theory that embraces such divergence and differences, not as the destination or summary of this journey. Based on the knowledge what can be seen as generalizable, we can now go on to specify the role and kind of uniqueness that is adding valuable insights to explain the role of context for EA.

Appendix 1

Table 4 Ambiguity

Element (Stam, 2015)	Relevance EE literature	Relevance determinant of EA literature	Examples of variables include
Networks	Network density in a spatial area is critical for the quality of the EE (Spigel, 2017)	Connecting to others is key to the entrepreneurial process, for example, for becoming a nascent entrepreneur (Davidsson & Honig, 2003), for venture performance (Batjargal, 2003), and for resource acquisition (Semrau & Werner, 2014)	Firm density (Backman, 2015); density of associational activity (Weiss et al., 2019)
Leadership	In EEs, a set of “visible” entrepreneurial leaders is seen as critical in building and maintaining the ecosystem (Stam, 2015). This happens through the diffusion of entrepreneurship-related knowledge through experienced entrepreneurs (Spigel & Harrison, 2018)	Role models can motivate others to become entrepreneurially active (Bosma et al., 2012)	Project leaders (Stam & van de Ven, 2021); share of high-growth firms (Audretsch & Belitski, 2021)
Finance	In the literature on EEs, the importance of regional financiers with knowledge of entrepreneurship is highlighted (Stam, 2015), but also a country’s capital market is relevant (Acs et al., 2014)	External financing is an important factor for the establishment, survival, and growth of new firms (Fotopoulos & Louri, 2000; Chowdhury & Maung, 2020)	Ease of getting credit (Awaworyi Churchill, 2017); number of VC investments (Li & Zahra, 2012)
Talent	Basis for the EE (Stam, 2015)	A diverse and skilled group of workers is positively associated with EA (Lee et al., 2004; Seth & Lee, 2017)	% bachelor’s degree (Dove, 2020); R&D employees in private firms (Mueller, 2007)
Knowledge	It provides the basis for opportunities for entrepreneurship (Spigel, 2017)	Knowledge generated by universities, companies, and R&D institutes positively influences (knowledge-intensive) EA (Audretsch & Lehmann, 2005; Colombelli & Quatraro, 2018)	Industry patents (Audretsch et al., 2012); no. universities (Baptista & Mendonça, 2010)
Support services/intermediaries	Lowering entry barriers in EEs (Stam, 2015)	Typical support services in the entrepreneurial context are incubators (Colombelli et al., 2021), accelerators (Audretsch & Belitski, 2021), or business consultancies (Stam and van de Ven 2021). Moreover, institutional conditions that aim at fostering EA provide a national framework for these supports (Acs et al., 2014; Audretsch et al. 2021)	Incubators (Colombelli & Quatraro, 2018); government entrepreneurship programs (Yan & Guan, 2019)

Table 4 (continued)

Element (Stam, 2015)	Relevance EE literature	Relevance determinant of EA literature	Examples of variables include
Formal institutions	In EEs, formal institutions provide the “rules of the game” (Audretsch et al., 2021)	Analyzing institutions and their impact on EA is a key research stream in understanding why EA differs systematically (Audretsch et al., 2019). Scholars found its influence on EA for example in terms of the legislative environment and rule of law (Levie & Autio, 2011), or regarding taxes (Braunerhjelm et al., 2021)	Corruption (Jauregui et al., 2020); rule of law index (Levie & Autio, 2011)
Culture	It supports and normalizes entrepreneurial actions in EEs (Feld, 2012; Spigel, 2017)	Cultural values and attributes play a major role in explaining differences in EA at the country level (Kashifa et al., 2010). Culture is often associated with an entrepreneurial climate (Goetz & Freshwater, 2001)	Uncertainty avoidance (Autio et al., 2013); self-employment rate, 1989 (Fritsch & Wyrwich, 2014)
Physical infrastructure	In the literature on EE frameworks, scholars argue that both on the regional and on the national level, physical infrastructure enables or constrains human interaction (Isenberg, 2010; Spigel, 2017; Stam, 2015)	Transportation access (Chatman et al., 2016), or broadband access (Alderete, 2017) can positively influence EA	Internet penetration rate (Kolokas et al., 2020); metropolitan city dummy (Iacobucci & Perugini, 2021)
Demand	Demand for new goods and services as well as market sizes provide opportunities and enable venture creation in EEs (Spigel, 2017; Stam, 2015)	The relationship between economic prosperity (e.g., GDP, value-added) and EA is proven (Wennekers et al., 2005; Verheul et al., 2009)	Population growth (Armington & Acs, 2002); GDP per capita (Avnimelech et al., 2014)

Appendix 2

Table 5 Research procedure

Research procedure adopted from Steel (2021)	
1. Research objectives	<ul style="list-style-type: none"> Identifying the design of the EE framework on the regional level Analyzing the relevance of the EE elements as antecedents of EA
2. Conceptual boundaries	<ul style="list-style-type: none"> Regional EE and regional factors that influence EA (Davidsson et al., 1994; Sternberg, 2011; Fritsch & Wyrwich, 2014; Audretsch, 2015) These regional factors, their interdependencies, can be understood as spatially delineated EEs that produce EA as an output (Stam, 2015; Stam & Spiegel, 2018; O'Connor et al., 2018; Wurth et al., 2021)
3. Search databases	<ol style="list-style-type: none"> Web of Science Scopus ProQuest
4. Search terms	<p>First string for entrepreneurial activity</p> <p>Second string for entrepreneurial ecosystem, and general entrepreneur-ship</p> <p>entrepreneur*, start?up, new business, new firm, new venture ecosystem\$, environment\$, system\$, infrastructure, activit*, entry\$, formation, creation</p>
5. Inclusion criteria	<ul style="list-style-type: none"> Study has at least one EA variable Study has at least one regional variable that could be assigned to the EE framework from Stam (2015) All studies of all types from the first record until October 2021
6. Exclusion criteria	<ul style="list-style-type: none"> Observational unit of the study is at the country or federal level Assigned variables have a high-order influence on EA (e.g., CO² emissions, climate conditions) Limited information about study characteristics and variables (source, definition, correlation coefficient and mean + standard deviation)
7. Encoding procedure	<ul style="list-style-type: none"> Unification of variable names, definitions, and sources Categorizing study methods, design, observational unit, and characteristics Grouping of variables with the same name, definitions, and measures into clusters Assignment of these clusters to the framework of Stam (2015) based on his definitions Formulation of a theory bases rationale and existing measures as benchmark (e.g., 25% of variables are across all studies the same measures previously used by of Stam (2015, 2018), Stam and van de Ven (2021), and Leendertse et al. (2022)) Intertemporal grouping and encoding discussions among the authors
8. Methodology	<ul style="list-style-type: none"> Random effects model as main model Three-layer meta-analysis regression analysis framework for robustness
9. Publication bias detection	<ul style="list-style-type: none"> Egger's regression Trim-and-Fill technique Rücker et al.'s (2011) limit meta-analysis method <i>p</i>-curve Three-layer MARA

Extra information: ? is to allow for –and letters in the middle of a word (e.g., start-up, start up, startup), \$ is used for one extra letter or basic form (e.g., system\$ returns system and systems), * is used to allow for multiple suffixes (e.g., entrepreneur* returns entrepreneur, entrepreneurial, entrepreneurship)

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Data availability The data that support the findings of this study are available from the corresponding author, upon reasonable request. The included studies are presented in the supplementary materials.

Declarations

Conflict of interest The authors declare no competing interests.

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