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Measuring entrepreneurial ecosystems across levels: a district approach

Sophia Hess · Andreas Wahl · Alan R. Johnson

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Abstract Entrepreneurial ecosystem measures should combine archival civic and self-reported entrepreneur data. This combination helps to overcome the limitations of aggregated archival data that affect our collective capacity to derive actionable insights for research and policy. Previous measurement approaches lack consistency with entrepreneurial ecosystem theory because they do not capture data at a sufficiently local level or data about entrepreneurs' values, beliefs, and attitudes. This paper proposes a new measurement approach for EE elements at the district level (NUTS-3), facilitating comparisons of local geographic EE properties and measuring relations between entrepreneurs, new ventures, and their ecosystems. Using confirmatory factor analysis, we combine self-reported and archival data to connect the micro and macro dimensions of the entrepreneurial ecosystem phenomenon. Analyzing survey data from 257 founders of innovative startups across 29 NUTS-3 districts in Baden-Württemberg, Germany, our findings support the “substitutability logic” among ten entrepreneurial ecosystem elements and uncover district-level geographic properties. Our study offers replication possibilities, recommendations for entrepreneurs' actions, and policy monitoring.

Plain English Summary Policymakers appear to “bend over backwards” to facilitate entrepreneurs, new ventures, and their local ecosystems with various interventions—but how to decide whether they make any difference? Researchers disagree about where to place the boundaries between entrepreneurial ecosystems. To compare one entrepreneurial ecosystem with another, we must decide *where* entrepreneurs and new ventures belong. Researchers over-relying on public archival data available for relatively large geographic areas, i.e., states (NUTS-1) or regions (NUTS-2), at the expense of survey data about entrepreneurs' values, beliefs, and attitudes gathered for smaller local areas, i.e., districts (NUTS-3), compound the problem. We propose to resolve the boundary problem with a new measurement approach. *First*, we gather self-reported and archival data at the district level. *Second*, we use systematic scale development procedures to validate congeneric measures that reflect EE elements. *Third*, the survey data helps to connect the micro and macro dimensions of EEs. Taken together, we move toward a measurement approach to reflect on whether local interventions can make a difference.

Keywords Entrepreneurial ecosystems · Measurement development · Construct validation · Confirmatory factor analysis · Spatial granularity

JEL Classification L26 · M13 · R58 · C18

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1 Introduction

Entrepreneurial ecosystem (EE) theory has consolidated over the last decade (Isenberg, 2010; Stam & Van de Ven, 2021) and more recently (Cho et al., 2022; Wurth et al., 2022, 2023). The EE offers researchers and policymakers a perspective on how new venture creation, economic growth, and regional development work and how to reinforce it through policy interventions (Colombelli et al., 2019; O'Connor et al., 2018; Stam & Spigel, 2018). EEs are defined as “a set of interdependent actors and factors that are governed in such a way that they enable productive entrepreneurship within a particular territory” (Leendertse et al., 2022, p. 1). EEs are explicitly systemic (Levie et al., 2014; Roundy et al., 2018), and the entrepreneur is not only the output but also a core part of the ecosystem (Auerswald & Dani, 2017; Stam, 2015). Furthermore, entrepreneurs and innovative startups with high growth aspirations are critical drivers of adaptive and enduring positive economic outcomes, rather than the large share of startups without innovative traits and growth ambitions (Cavallo et al., 2021; Shane, 2009; Spigel & Harrison, 2017).

However, productive entrepreneurship is more than just a local event (Andersson & Henrekson, 2015; Feldman, 2001) because it can vary considerably between neighboring localities (Fritsch & Wyrwich, 2014; Perugini, 2023). To investigate the geographic properties¹ of EEs (Audretsch & Belitski, 2021) and to measure relations between entrepreneurs, new ventures² and their local ecosystems (Roundy & Lyons, 2023), we need to disaggregate to a more fine-grained level of observation (Bruns et al., 2017). Valid measures and data are needed to predict variation and interdependencies between EE actors and factors, test hypotheses, and monitor the effects of policy changes on entrepreneurial outputs and economic outcomes at a more granular scale (Audretsch & Belitski, 2017; Stam & Van de Ven, 2021; Roundy & Lyons, 2023).

Research aimed at understanding the configurations, mechanisms, and evolution of EEs reaches from extensive archival analyses (Andrews et al., 2022; Buratti et al., 2023; Johnson et al., 2022) and survey analyses (Farhat et al., 2017; Reynolds, 2009) to detailed qualitative approaches (Muñoz et al., 2020; Rocha et al., 2021). Additionally, studies have pointed to the local but also multilevel and nested character of EEs (state-region-district; entrepreneur-firm-ecosystem), exhibiting distinctive characteristics and entrepreneurial activity in various spatial contexts, with different EE elements manifesting at different levels of spatial aggregation (Audretsch & Belitski, 2021; Stam & Welter, 2020; Welter, 2011). On the other hand, measurement approaches for EE have started to become more fine-grained spatially, from states and regions (Acs et al., 2014; Leendertse et al., 2022) to districts (Cavallo et al., 2023; Perugini, 2023; Roundy & Lyons, 2023).

Nonetheless, most empirical studies tend to take a macro perspective, focusing on multiple aggregated data sources (NUTS-1, NUTS-2)³ (e.g., Leendertse et al., 2022), neglecting the micro-foundations of EEs (Cosenz et al., 2023; Roundy & Lyons, 2023). Therefore, *first*, if we over-rely on data for states or regions, then we (1) ignore additional heterogeneity of entrepreneurial activity and spatial patterns at the NUTS-3 district level and (2) lack explanations of connections between entrepreneurs, new ventures, and their local ecosystems (Cavallo et al., 2021). *Second*, while two measurement streams have evolved in the literature, focusing on individual-level or regional-level analyses, current measurement approaches often use single-sourced measures based on either aggregated archival data⁴ (e.g., Andrews et al., 2022) or self-reported data (e.g., Corrente et al., 2019; Liguori

¹ Geographic properties refer to spatial contexts and spatial boundaries of EEs, which exhibit different characteristics and EE element configurations.

² The term “new ventures” refers to various types of emerging entrepreneurial activities in general. However, in this paper, we refer to one type of new venture, namely innovative, growth-oriented startups.

³ NUTS (Nomenclature of Territorial Units for Statistics) is the European geocode standard for referencing subdivisions of countries for statistical purposes in the EU. Territories are divided into three levels: NUTS-1 identifies major socio-economic regions, NUTS-2 are basic regions for the application of regional policies, and NUTS-3 are small regions for specific diagnoses (<https://ec.europa.eu/eurostat/web/nuts/background>). In what follows, we refer to NUTS-1 as “states,” NUTS-2 as “regions,” and NUTS-3 as “districts.” NUTS territorial units also correspond to sub-national geo-political decision-making jurisdictions at the state, region, and district levels.

⁴ The term “archival data” refers to publicly available archival data, e.g., Eurostat data, OECD data, and others.

et al., 2019; Nicotra et al., 2018). Studies relying exclusively on archival or self-reported data fail to reduce potential bias from single data sources (Campbell & Fiske, 1959). *Third*, despite the emergence of empirical studies at the more granular NUTS-3 level, there is still inconsistency with EE theory (e.g., Cavallo et al., 2023; Perugini, 2023), as they (1) do not comprehensively capture all ten EE elements or (2) do not reflect entrepreneur- and firm-specific factors in the measurement (Cosenz et al., 2023). This inconsistency results in an incomplete understanding of EEs, especially in contexts with significant territorial differences in startups and business growth, where more granular measures and data become essential (Perugini, 2023).

To answer the open controversies in EE research, we first must address methodological challenges toward EE measurement at the NUTS-3 level. We concur with Audretsch and Belitskis' (2017) view that entrepreneurial activity needs to be studied locally, where decision-making, individual characteristics, limited research, and data availability play a significant role and where we can take advantage of smaller observation units (Feldman & Lowe, 2015). The challenge is to build measures that combine micro dimensions—bottom-up (e.g., entrepreneurs' values, beliefs, and attitudes), with macro dimensions—top-down (e.g., EE elements), to enable a more comprehensive perspective on EEs (Cosenz et al., 2023). However, identifying measures on a more micro-level is complex as the spatial level of EEs is often constrained by data availability (Feldman & Lowe, 2015; Nicotra et al., 2018).

In this paper, we propose a new measurement approach based on NUTS-3 geographic granularity, which the EE research program needs to improve internal validity (Cook & Campbell, 1979). Without a more fine-grained district measurement approach, empirical research runs the risk of comparing arbitrary numbers of urban districts “smushed” with arbitrary numbers of rural districts (Hoffman, 2015). We use confirmatory factor analysis (CFA) and systematic scale development procedures to evaluate, select, and combine measures (Brown, 2015; Little, 2023). Our approach can assess the validity and reliability of existing measurement instruments (e.g., Leendertse et al., 2022) and includes statistical tests for alternative hypotheses about (1) EE configurations and (2) the “substitutability” versus “completeness logic” of

EE elements at the NUTS-3 level. *Finally*, our measurement approach integrates survey data about entrepreneurs' values, beliefs, and attitudes (micro, bottom-up) with archival data available on the NUTS-3 level (macro, top-down) to create a validated set of indicators that reflect all ten EE elements posited by existing theory. The survey data helps us to overcome archival data granularity limitations and to reduce biases arising from contamination and deficiency in measurement approaches (McCloy et al., 1994), which are alleviated when additional sources can be tapped.

Our study is based on a sample of 257 founders of innovative startups from Baden-Württemberg (BW), Germany, using observations from 29 districts. We show that a first-order baseline measurement model including ten EE elements has an acceptable model fit and supports the “logic of substitutability” (Schrijvers et al., 2024; Spigel, 2017; Zhao et al., 2023). Our paper is part of an emerging discourse about the measurement of EE. We further the literature by providing a new measurement instrument with a validated set of 45 indicators, combining self-reported data (bottom-up) and archival data (top-down) at the NUTS-3 level. This method facilitates a more nuanced perspective on EE and bridges the micro- and macro-foundations of the EE phenomenon (Cosenz et al., 2023; Kapturkiewicz, 2022). This approach allows researchers to *first* measure relations between entrepreneurs and their local ecosystems, reflecting the multilevel character of EEs. *Second*, it helps generate concrete, empirically validated recommendations for entrepreneurs. *Third*, it allows policymakers to propose and monitor district-level interventions influencing EE elements, as NUTS-3 districts correspond to geo-political jurisdictions with high self-regulation.

2 Theory

2.1 Entrepreneurial ecosystem perspectives

Drawing on the earliest works of Isenberg (2010), Stam (2015), and Spigel (2017), the EE approach has gained theoretical and practical relevance (Cavallo et al., 2021; Cho et al., 2022) to understand how EEs ignite productive entrepreneurship, economic development, and social well-being in a country, region,

and city (Colombelli et al., 2019; Colombo et al., 2019; Theodoraki et al., 2022). Despite the progress made by EE scholars, the EE concept has a tacit tendency in entrepreneurship theory to emphasize more macro-, ecosystem-level dynamics rather than explaining more explicit micro-mechanisms linking entrepreneurs, new ventures, and the local ecosystem (Felin & Foss, 2023; Roundy & Lyons, 2023). However, we still lack a detailed understanding of *how* things happen within ecosystems (Wurth et al., 2023) and *how* core actors perceive EE elements (Felin & Foss, 2023). As a result, EE research has struggled to generate concrete and empirically validated recommendations for entrepreneurs and policymakers (Roundy & Lyons, 2023).

Research discussions on understanding the EE phenomenon reach from extensive analyses of archival data (Andrews et al., 2022; Lafuente et al., 2022) or extensive surveys on a more macro-level (Farhat et al., 2017; Reynolds, 2009) to detailed qualitative investigations (Muñoz et al., 2020; Rocha et al., 2021). Still, much of the quantitative empirical literature focuses on highly aggregated data available in administrative units, mainly NUTS-1 and NUTS-2 (Nicotra et al., 2018), for example, historical GEM data (Bruns et al., 2017), national governmental data (Auerswald & Dani, 2017; Vedula & Fitza, 2019), or Eurostat data (Leendertse et al., 2022; Schrijvers et al., 2024). Consequently, previous research suffers from a mismatch between macro-level inputs (e.g., EE elements) and micro-level outcomes (e.g., innovative startups), neglecting the heterogeneity of entrepreneurial activity and the geographic properties of EEs from a more micro perspective (Audretsch & Belitski, 2021; Cosenz et al., 2023). Using the NUTS-1 and NUTS-2 levels of analysis limits understanding of how issues unfold at a localized spatial scale (Rammer et al., 2020). Furthermore, focusing on EEs as the central unit of analysis draws attention away from the founder- or firm-specific factors at the core of every ecosystem (Cosenz et al., 2023; Felin & Foss, 2023).

Research on entrepreneurship-in-context has underscored the importance of the NUTS-3 districts as a significant unit of analysis (Andersson & Henrikson, 2015; Feldman, 2001; Neumeyer et al., 2019; Welter, 2011). Despite the ongoing processes of digitization and globalization (Autio, 2017; Cavallo et al., 2021, 2023), the local dimension remains a crucial

aspect of entrepreneurship. Audretsch and Belitski (2021), for example, argue that the NUTS-3 districts constitute sufficiently large geographic areas to represent an EE within a region statistically and that the NUTS-3 level is a better unit of analysis compared to large European NUTS-2 regions (Friesenbichler & Hölzl, 2020; Perugini, 2023; Roundy & Lyons, 2023).

So far, two rival causal logics dominate the EE research field: (1) the “logic of completeness” (Acs et al., 2014; Lafuente et al., 2022), which states that all elements need to be present and the weakest link builds the most critical constraint; (2) the “substitutability logic” (Corrente et al., 2019; Spigel, 2017; Zhao et al., 2023), which states that elements are to some extent substitutable, and hence, there can be multiple element configurations for a high-performing EE. Schrijvers et al. (2024) conclude that there is not one perfect configuration that all successful EEs exhibit, but for very high-performing EEs, having only a few elements on a high level is not sufficient, and therefore propose a combination of the “completeness and substitutability” logic. Cavallo et al. (2023) argue that although various EE types exist, EE element configurations are more “balanced” than “polarized” (i.e., one or more dominant EE elements exist). However, more empirical research is needed to investigate the precise configuration of the “substitutability” versus “completeness” logic.

Since EEs are continuously evolving and are not limited to any industrial sector (Cavallo et al., 2021), their boundaries still need to be determined (Stam & Van de Ven, 2021). EE literature has recognized (1) that causal mechanisms between actors and factors in entrepreneurial activities occur at different spatial levels of analysis (Audretsch et al., 2019) and (2) that spatial contexts are nested (i.e., state-region-district), considering the EE as a geographically bounded entity (Perugini, 2023). Therefore, *first*, if we understand entrepreneurship as a local event and entrepreneurs as agents who actively shape and are shaped by their local environment (Feldman, 2001; Welter, 2011), then increased geographic granularity can help observe the hypothesized relations in the EE literature (Audretsch & Belitski, 2021). *Second*, given the multilevel character of EEs (state-region-district; ecosystem-firm-entrepreneur), we should try to understand ecosystem configurations at the most fine-grained level of analysis (Rocha et al., 2021), drawing more attention to entrepreneur- or firm-specific

factors (bottom-up) and connecting them with EE macro dimensions (top-down) (Cosenz et al., 2023). We need to understand both the macro- and micro-foundations of EEs to develop a theory that comprehensively depicts an ecosystem perspective (Roundy & Lyons, 2023).

2.2 Measuring entrepreneurial ecosystems

Besides critical conceptual challenges in defining the nature and configuration of EEs, the measurement of EE involves the empirical challenge of consistently assessing EEs across different entrepreneurs and firms, places, and times (Wurth et al., 2022, 2023). Current approaches, models, and means of assessment should account for the diversity of local EEs, which is problematic when selecting proxies for measuring EE elements, outputs, and outcomes (Kuratko et al., 2017). The question of how to measure EEs has only recently begun to gain attention as scholars and policymakers aim to improve the precision of models for innovation and entrepreneurship policies (Cavallo et al., 2021; Johnson et al., 2022). To date, two measurement streams have evolved in EE literature: (1) individual-level and process-based studies, taking a more *bottom-up*, qualitative perspective (Corrente et al., 2019; Liguori et al., 2019; Rocha et al., 2021) and (2) regional studies, measuring causal relations between EEs and productive entrepreneurship *top-down*, using single or multiple index proxies and large archival datasets (Vedula & Fitza, 2019; Stam & Van de Ven, 2021; Leendertse et al., 2022; Schrijvers et al., 2024).

Individual-level studies often use aggregated GEM data to analyze EEs and, therefore, face an expert evaluation bias. For example, Corrente et al. (2019) use stochastic multicriteria acceptability analysis to evaluate and compare EEs, Nicotra et al. (2018) assess causal relations between ecosystem factors and outputs based on GEM data, and Muñoz et al. (2020) examine EE configurations based on local expert evaluations. Others, for example, Liguori et al. (2019) demonstrate how EEs can be assessed using perceptual measures of entrepreneurs related to their surrounding ecosystem and, therefore, lack more objective archival measures that could complement self-reported data to gain a more objective understanding of the EE phenomenon (Cavallo et al., 2021).

On the other hand, some regional studies provide distinct measurement frameworks, such as a conceptual framework to merge public archival datasets with relational database management techniques to uncover firm-government relationships (Johnson et al., 2022). Others combine state-level business registrations with a predictive analytics approach to characterize the quality and quantity of entrepreneurial performance (Andrews et al., 2022). However, these approaches only focus on aggregated archival data, failing to combine archival with self-reported data on, for example, entrepreneurs' values, beliefs, and attitudes.

In contrast, measurement approaches by Stam and Van de Ven (2021) or Leendertse et al. (2022) combine multiple data sources (e.g., Eurostat, Global Entrepreneurship Monitor, European Social Survey), following an index-based approach to measure EEs on a NUTS-2 level. Nonetheless, these approaches operate on a more aggregated macro-level, ignoring the heterogeneity of entrepreneurship and spatial patterns at a more micro-level. Still, even at aggregated levels (NUTS-1, NUTS-2), there is a need to merge national with regional data. Consequently, the strengths and weaknesses of the *local* system cannot be captured, and policymakers struggle to identify key action points (Jung et al., 2017). Additionally, index-based approaches fall short of evaluating the latent factor structure of the measurement instruments and their fit to the data (Brown, 2015; Little, 2023).

Even studies measuring EEs on the NUTS-3 level, for example, Cavallo et al. (2023) or Perugini (2023), need more direct measures (i.e., from surveys) to understand connections between entrepreneurs and their local ecosystem. Despite the progress made by scholars empirically investigating the micro-foundations of EEs, such as Cosenz et al. (2023) introducing an alternative method to frame EEs through critical causal interdependences, recent micro- or NUTS-3 level measures are only partly consistent with EE theory, capturing only some EE elements provided in the EE framework by Stam and Van de Ven (2021). Finally, the generalizability across different entrepreneurs, firms, places, and times remains to be shown.

Although EE measurement has started to consolidate, becoming more fine-grained spatially, from the NUTS-1 state (Acs et al., 2014) to the NUTS-2 region (Leendertse et al., 2022) and now NUTS-3 district level (Andersson & Henrekson, 2015; Cavallo

et al., 2023; Perugini, 2023; Rocha et al., 2021), the majority of measurement approaches still focuses on archival data and macro-level measures. We concur with Cosenz et al. (2023) that the challenge is now to connect *top-down* (macro-foundations) with *bottom-up* (micro-foundations) dimensions while being consistent with EE theory (Stam & Van de Ven, 2021).

In the quest for answers to unresolved controversies in EE research, we first must address current shortcomings and methodological challenges of EE measurement. First, as we lack comprehensive publicly available archival data at the NUTS-3 level, we cannot directly transpose all existing measures from NUTS-1 or NUTS-2 to a more granular NUTS-3 level without dropping essential elements in the EE approach by Stam and Van de Ven (2021). Second, EE research suffers from archival data limitations in capturing the micro-foundations of the EE phenomenon and integrating the entrepreneur into the measurement equation (Perugini, 2023; Roundy & Lyons, 2023). To overcome archival data constraints at the NUTS-3 level and enrich EE theory, we propose the following research question: *How can we overcome archival data granularity limitations to enable a NUTS-3 measurement approach for EEs aligned with its theoretical foundations?*

To answer this research question, we propose a new measurement approach—building upon the work of Leendertse et al. (2022)—which enables us (1) to overcome archival data granularity limitations at the NUTS-3 level, (2) to measure relations between entrepreneurs and their local ecosystem, and (3) to compare local geographic properties of EEs. We do so by enriching existing archival data at the NUTS-3 level (top-down) with self-reported data about entrepreneurs' values, beliefs, and attitudes (bottom-up), thereby paving the way to connect the micro and macro dimensions of the EE phenomenon. Our approach improves the sensitivity of existing measures while ensuring theoretical consistency with the EE approach at a lower level of spatial aggregation.

3 Methods

3.1 Empirical setting

In this paper, we report on data collected between July and August 2022 from founders of innovative

startups in Baden-Württemberg (BW), one of the 16 federal states (NUTS-1) located in the southwest corner of Germany, containing four regions (NUTS-2) and 44 districts (NUTS-3) (Eurostat, 2021). We build on previous empirical EE research operationalizing productive entrepreneurship with the number of innovative, growth-oriented startups (Corrente et al., 2019; Stam & Van de Ven, 2021; Andrews et al., 2022) and apply the definition by Sternberg et al. (2019) to access our target population: The startup has (1) an innovative product, service, or technology; (2) an intention to grow and scale; (3) a potentially high impact on the regional economy; and (4) high employee growth. We align with Leendertse et al. (2022) and only account for startups that are 5 years old or less. Innovative and growth-oriented entrepreneurship is increasingly emphasized in the entrepreneurship literature (Cavallo et al., 2021; Henrekson & Sanandaji, 2014; Mason & Brown, 2014; Spigel & Harrison, 2017), and startups are one type of productive entrepreneurship, besides various others (e.g., scale-ups, unicorns). Innovative startups are particularly interesting, as they have the potential to generate an impact on the economy, technology, and society in the long term (Acs & Mueller, 2008) and are positively related to job creation (Fritsch, 2013).

With its 11 million inhabitants, Baden-Württemberg has about 3274 active, innovative startups founded since 2018, of which around 2425 (74.07%) are registered (CR, 2022) and another 849 (25.93%) are early-stage. Teams founded the majority of these startups (88.1%) and solo entrepreneurs the remainder (11.9%). On average, the startups in BW are 2.3 years old (Freudig, 2020). These startups receive support from various public policies and programs the local government implements (e.g., state-funded accelerators). The unique features of BW cover its high potential for early-stage startups, a decentralized topology with several medium-size cities, a thriving corporate industry sector, and increasing data availability, making it an interesting setting for conducting EE research that can generalize to other contexts that do not enjoy significant agglomeration effects, i.e., a large city, e.g., Berlin.

We conducted the survey over 6 weeks, between July 6 and August 17, 2022. We applied a non-probability sampling method, i.e., convenience sampling, where we selected founders from the whole startup population of BW who participated in startup

programs hosted by two local support institutions (subjective method). Non-probability sampling has two major advantages: (1) response rates increase due to the founders' commitment to personal contacts, and (2) data collection cost is lower compared to probability sampling. However, non-probability approaches must address potential selection bias and representativeness issues (Scheaf et al., 2023). Given our focus on methodological advancement of EE measures, as opposed to empirical testing of substantive hypotheses, we submit that potential selection biases and representativeness issues are less of a concern.

We contacted 643 founders across Baden-Württemberg (314 early-stage; 329 registered startups). After three reminders, the overall response rate was 40% (257 responses), from which 152 (59.1%) fully completed the survey. The average duration to complete the survey was 24 min (median=20 min). Our study sample contains 257 founders who started businesses between 2018 and 2022 (19.8% early-stage projects; 80.2% registered startups: pre-seed or seed stage; firm age $M=2.4$ years). Most founders are males (83.3% m; 16.7% f), and their ages range between 25 and 35 years. Most founders are German (90%), and most founded their company with co-founders (80%; 20% solo; $M=2.3$ founders per startup). The descriptives for our sample show characteristics similar to those of the population in Baden-Württemberg. Our sample covers 29 out of 44 possible districts in Baden-Württemberg. Nevertheless, one consequence of our convenience sampling strategy is that most startups are located in Stuttgart ($N=114$, 44.4%). Figure 1 illustrates the spatial distribution of our observations across Baden-Württemberg.

3.2 Dataset creation and item selection

This paper combines multiple data sources to develop credible and accurate metrics for EEs at the district level (NUTS-3). Since no dataset combines publicly available archival measures on the NUTS-3 level with self-reported data from founders, we propose one. Where possible, we draw on items from previously validated measurement instruments. For example, our entrepreneurial culture questions include entrepreneurial motivation items from the Global Entrepreneurship Monitor (GEM, 2018). In addition, we build on already existing regional studies with

entrepreneur-specific metrics in Europe (e.g., World Bank, 2020). These studies are used as item sources but lack district granularity and require some adaptation to this context (Little, 2023).

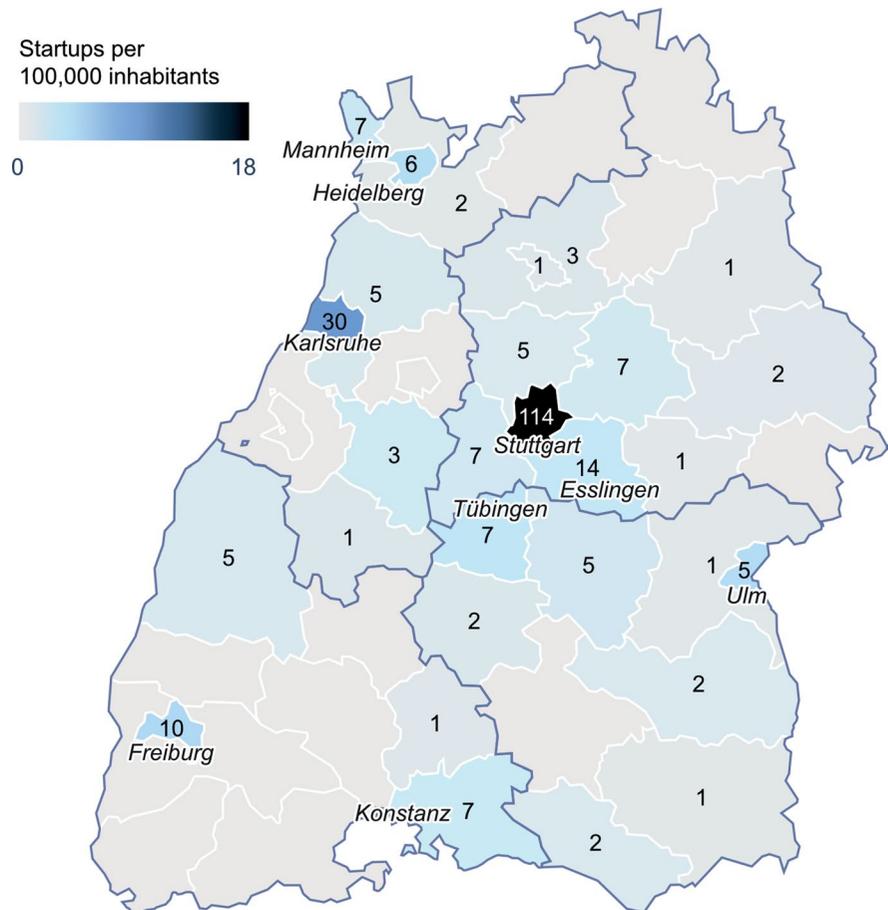
The indicators we test build on the EE conceptual framework proposed by Stam and Van de Ven (2021). We broadly adopt the constitutive definitions for ten EE construct elements from Leendertse et al. (2022) and adapt their operational definitions to the NUTS-3 observation unit (see Appendix Table 4). We use survey data (*founder level*, e.g., motivation to start a business), web-scraped data (*firm level*, e.g., number of research centers per district, number of early-stage startups), and publicly available archival data (*district level*, e.g., share of unemployed individuals, GDP) to develop valid and reliable measures for EE elements at district granularity.

We expand the canon of EE measurement approaches by developing a novel set of indicators that allow us to integrate entrepreneurs' values, beliefs, and attitudes with existing archival measures to gather higher-resolution data for each of the ten EE elements. Thus, (1) we include indicators adapted from other survey instruments, allowing for a more founder- and firm-centric perspective. (2) We perform context-specific adaptations to previously validated archival measures to achieve increased geographic granularity (NUTS-3). (3) We combine self-reported data from entrepreneurs with publicly available archival data and (4) validate the applied transformations through CFA. We set a target number of survey items according to Kenny's rule of thumb (1979, p. 143),⁵ aiming to include three to six reasonable measures per EE construct element from each source.

We started our systematic scale development with 84 indicators across the ten EE elements (see Appendix Table 9). We collected both survey and archival data for eight elements: formal institutions, entrepreneurial culture, social networks, financial resources, new knowledge, workforce talent, local demand, and intermediate services. We used survey data for the intermediate services element to overcome archival data granularity constraints at the NUTS-3 level with indicators used in previous studies (e.g., percentage employment

⁵ Kenny's rule of thumb about the number of indicators is as follows: "Two might be fine, three is better, four is best, and anything more is gravy" (Kline, 2023, p. 234).

Fig. 1 Study observations per 100,000 inhabitants for NUTS-3 districts in Baden-Württemberg, Germany



Note. The thin white lines show district (NUTS-3) boundaries. The absolute number of observations is shown for the 29 district areas out of 44 possible. The heat map shows the number of startups per 100,000 inhabitants for each district where we have respondents. The bold blue lines show region (NUTS-2) boundaries. We also label other districts that show up as ‘startup hot spots’ in the population, e.g., Heidelberg, Ulm.

in knowledge-intensive market services, Eurostat). We used the same Eurostat (Regional Competitiveness Index) items as Leendertse et al. (2022), available on the NUTS-3 level for the physical infrastructure element. We did not opt to gather survey data for this element, as the archival measures have been previously validated and shown to be effective in capturing territorial differences in related studies. In contrast, we prioritized survey data for the community leadership element to enhance measurement precision, aiming to reflect the element, as conceptualized by Stam and Van de Ven (2021), detailed in Appendix Table 4.

After evaluating, selecting, and combining items using CFA, we end up with 45 indicators in our measurement model (Appendix Table 5). We excluded some indicators that violated *convergent* validity criteria, such as “We have active customers that buy

our product, technology, services,” with the expected focal element, for example, *local demand*, showing cross-loading with another element. The same applied to indicators for *community leadership*, such as “I have certified project management skills,” “I have an MBA,” and “I have a leadership position in voluntary work,” which also exhibited cross-loadings. Other indicators were excluded because of low variance in the data, such as “Disposable income per capita in a district” and “Number of passenger flights.”

Finally, our approach captures (1) the financial resources, new knowledge, and workforce talent elements through a combination of survey and archival data; (2) the formal institutions, entrepreneurial culture, social networks, leadership, and intermediate services elements with survey data only, because archival data was not sufficiently informative; and (3) the physical

infrastructure and local demand elements solely using archival data, with tested survey items for local demand that deemed non-informative. However, the ten latent construct elements are not considered in isolation. Instead, the overall integration of archival and survey data stems from including each construct within a single statistical model using either the undirected correlations among the constructs or an additional second-order construct. By combining archival and self-reported data, we ensure unified spatial scales (NUTS-3) for all items included in the model, thereby eliminating the need for mixed item scales (see, for example, Leendertse et al., 2022; Schrijvers et al., 2024). Table 1 presents the 45 indicators we used, and the respective descriptive statistics are presented in Appendix Table 5.

4 Results

4.1 Analytical strategy

We test our EE measurement approach using CFA to examine the latent structure of our test instruments, i.e., from survey data and archival data, and to evaluate the number of underlying factors produced by the indicators, i.e., factor loadings and residuals (Brown, 2015). Following Stam and Van de Ven (2021), the EE framework is understood as a multi-dimensional theoretical construct—the ten elements—that (1) build an interdependence web, which is equivalent to the EE construct, or (2) may combine in some way to form an overarching EE construct. A strength of the CFA approach to construct validation is that *convergent* and *discriminant* validity estimates are adjusted for error,⁶ including random error and method artifacts, such as archival data versus survey data, thus producing more reliable inputs for further analyses (Brown, 2015). We use CFA (1) to assess *convergent* and *discriminant* validity for items to tap each of the ten construct elements and (2) to specify a factor structure with an acceptable fit to the data. Once an acceptable measurement model is established, scholars can test and evaluate hypothesized relations between factors (Anderson & Gerbing, 1988), i.e., correlations

between EE elements or some criterion variable, such as output or outcome, regressed on the EE elements.

Figure 2 illustrates two hypothesized measurement models from the EE literature (Schrijvers et al., 2024): (1) the first-order measurement model in solid lines with all ten interdependent EE elements (non-hierarchical, supporting the “logic of substitutability”) (Spigel, 2017; Zhao et al., 2023), and (2) the hypothesized second-order EE construct in dashed lines (hierarchical, supporting the “logic of completeness”) (Acs et al., 2014).

We report the iterative steps to implement systematic scale development to reflect ten EE elements using CFA. We aim to provide a relatively small validated set of indicators that (1) keeps the instrument simple and understandable and (2) makes the instrument generalizable to other contexts, i.e., founders and firms, places and times, and, importantly, reproducible by other scholars with modest research resources. Our descriptive statistics (M, SD, skewness, kurtosis; Table 5) show univariate normal distributions for all indicators included in the analysis. Before our analysis, we performed three data manipulation steps: *First*, we adjusted district-sensitive variables for NUTS-3 population density, for example, “Value of government subsidies per district (EUR)” or “Share of total population per district that completed tertiary education.” *Second*, we recoded three variables into a dichotomous (yes, no) scale: “We have participated in multiple accelerator/incubator programs,” “We receive support from an external consulting firm,” “We are using external offices, labs, maker spaces, mentors, coaches, university facilities to develop our business.” *Third*, we transformed all variables from zero to one to align variables anchored by dichotomous (yes, no) or continuous scales (1 to 9; district-sensitive and non-district-sensitive items) (Little, 2023).

In our sample of 257 founders, 46.4% of responses had some missing values, and Little’s test (Little, 1988) reveals that missing values are not missing completely at random (MCAR). However, we can assume the missing data mechanism is ignorable (i.e., missing at random; MAR) because our questions are not socially sensitive or shaming.⁷ We opt for Direct-ML as a method to deal with the missing data because considerable evidence exists that it—even under high rates of missingness—produces estimates that are less

⁶ *Convergent* validity is the extent to which indicators of theoretically similar constructs are strongly correlated, i.e., indicators load onto the intended factor. *Discriminant* validity is the extent to which indicators of theoretically distinct constructs are weakly correlated, i.e., indicators do not load onto other unintended factors (Brown, 2015).

⁷ The missing mechanism and the high rate of missingness do not allow for estimating the model with only complete cases (Little & Rubin, 2002).

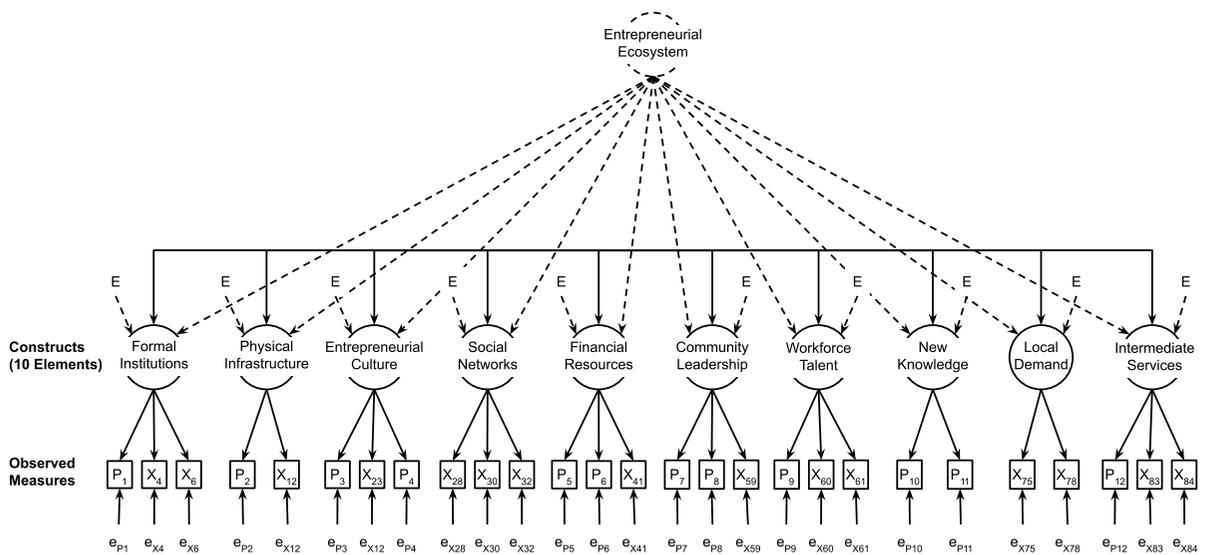
Table 1 Operationalization of the entrepreneurial ecosystem elements and output

Construct label	Operational definition	Item source	Data source
Formal institutions	In our district, some people get advantages from their education. ^(*) In our district, local regulations are an obstacle to starting a business. ^(*) In our district, registering property is an obstacle. ^(*) In our district, tax rates slow down business growth. ^(*)	WBDBR	BWS
Physical infrastructure	Population accessible within 1h30 by road in a district, as share of the population within a 120 km radius. ^(****) Population accessible within 1h30 by rail in a district, as share of the population within a 120 km radius, combined with short walk. ^(****) Population accessible within 1h30 by rail in a district, as share of the population within a 120 km radius., combined with short bike ride. ^(****) Highest speed of broadband connection available by local administrative unit in a district. ^(****)	Eurostat RCI	Eurostat RCI
Entrepreneurial culture	We are building a startup to take advantage of the business opportunity. ^(*) We are building a startup because we search for independence. ^(*) We are building a startup to increase personal income. ^(*) The entrepreneurial culture in our district encourages a) risk taking, b) creativity, and supports c) individual success, d) individual way of life. ^(*)	GEM	BWS
Social networks	Ties to other firms for collaboration. (e.g., SMEs). ^(****) Ties to other startup founders for collaboration. ^(****) Ties to entrepreneurial support organizations, providing resources to develop the business (e.g., knowledge, money). ^(****)	RIS/EIS	BWS
Financial resources	In our district, there are sufficient government subsidies available. ^(*) In our district, there is sufficient equity funding available. ^(*) In our district, there is sufficient debt funding available. ^(*) In our district, there is sufficient funding from informal investors available. ^(*) We access professional funding. ^(**) We access public funding. ^(**) Value of government subsidies per district (EUR). ^(****)	IE	BWS BMBF
Community leadership	We take actions that go beyond firm-level activities. ^(*) We regularly attend startup events in our district. ^(*) We collaborate with other founders to guide regional development. ^(*) We provide other actors with a vision to work toward. ^(*) Our activities contribute to higher recognition of entrepreneurial activities among policymakers. ^(*)	Stam and Van de Ven (2021)	BWS
Workforce talent	Developing new ideas is important to us. ^(*) Doing things on our own is important to us. ^(*) Being creative is important to us. ^(*) I have founded another startup before. ^(**) Share of total population per district that completed tertiary education. ^(****)	Eurostat	BWS BWSSO
New knowledge	We have applied for patents. ^(**) Value of R&D expenditure per district (EUR in bn). ^(****) We have published peer-reviewed articles. ^(**) Number of research centers per district. ^(****)	Eurostat	BWS
Local demand	Potential market size in Gross Domestic Product (GDP) per capita in a district. ^(****) Share of unemployed individuals in a district. ^(****)	Eurostat	BWSSO

Table 1 (continued)

Construct label	Operational definition	Item source	Data source
Intermediate services	We have participated in multiple accelerator/incubator programs. ^(**) We believe that being part of accelerator/incubator programs helped us to reach our goals faster. ^(*) We receive support from an external consulting firm. ^(**) We are using external offices, labs, makerspaces, mentors, coaches, university facilities to develop our business. ^(**)	CB	BWS
Productive entrepreneurship	Number of innovative startups per district. ^(***)	CB	CB; CR

(*)9-point scale: agree-disagree; (**)binary (y,n); (***)district-sensitive items adjusted for NUTS-3 district population density; (****)non-district-sensitive items. *WBDBR*: World Bank Doing Business Report; *BWS*: BW Survey; *RCI*: Regional Competitiveness Index; *BMBF*: Federal Ministry of Education and Research; *RIS/EIS*: Regional/European Innovation Scoreboard; *BWSSO*: State Statistic Office BW; *IE*: Invest Europe; *CB*: Crunchbase; *CR*: Commercial register BW



Note. The path diagram shows: 1) the hypothesized first-order measurement model (solid lines)—baseline model and 2) the second-order measurement model (dashed lines)—alternative hypothesis. Circles represent unobserved latent constructs. Rectangles represent measured indicators (‘X’ for indicators or ‘P’ for parcels). Single-headed arrows labeled by ‘E’ are disturbances, or ‘e’ are error variances. Straight single-headed arrows from circles to rectangles are expected factor loadings. Square double-headed arrows are covariances between first-order factors (drawing conventions: Little, 2023).

Fig. 2 Hypothesized measurement models

biased, more reliable, and above all, very close to the population model (Enders, 2001; Newman, 2003). Furthermore, Direct-ML has additional favorable properties for empirical datasets, including robustness to non-normality and observed variables anchored by different scales (Wahl, 2020).

We performed CFAs for each first-order EE element to discern (1) if we have achieved an acceptable

model fit and (2) if we have achieved the required *convergent* and *discriminant* validity with our selected set of indicators. Furthermore, we use parceling as a pre-modeling strategy (1) to trim down the number of indicators, (2) to create more reliable measures, i.e., lower indicator-to-sample size ratio, reduce sources of parsimony error, and (3) to manage most cross-loadings and correlated residuals (Little

et al., 2022). *First*, we execute *purposeful parceling* to eliminate cross-loadings and correlated residuals, which are prompted by modification indices that show pronounced decreases in the chi-squared statistic from freely estimating an additional parameter. *Second*, we follow a *balanced parceling* strategy, pairing items with high and low loadings. For model identification reasons, we opt for at least three items or parcels per factor so that each element is reflected by a just-identified model, which improves model stability when we put the sub-scale pieces together.

Past theory and evidence, especially from Stam (2015) and Stam and Van de Ven (2021), provide a compelling rationale to specify a ten-factor CFA, a priori, without running an exploratory factor analysis (EFA). To evaluate the acceptability of the CFA solution, we consider three main aspects: (1) overall goodness of fit, (2) specific points of ill fit, and (3) the interpretability, size, and significance of factor loadings (Brown, 2015). We chose “acceptable” fit as our threshold criteria to interpret fit indices because, to our knowledge, this is the first time CFA has been applied to an EE measurement instrument. Adopting guidelines by Hu and Bentler (1999), “acceptable” model fit for the main fit indices is defined as follows: RMSEA (≤ 0.08 , 90% CI below 0.08), SRMR (close to 0.08), CFI and TLI (in the range 0.90 to 0.95) (also see Brown, 2015). After establishing an “acceptable” fit for the ten elements separately, we integrate them into the two hypothesized models (see Fig. 2). First, we specify Model 1, the first-order CFA, as a baseline model (see Appendix Table 6). Second, we specify Model 2 with the EE as a second-order factor as an alternative hypothesis (see Appendix Table 7). Table 2 shows model fit indices for these two models.

Each of the goodness of fit indices in Table 2 suggests that our first-order measurement model (Model 1) with ten EE elements has an “acceptable” model fit—RMSEA=0.037 (90% CI=0.027–0.046, CFI=0.991), SRMR=0.084, CFI=0.927, and TLI=0.908—and has a better fit to the data on all fit metrics than the second-order model with the overarching EE factor (Model 2). The significant chi-squared difference test ($\chi^2_{(36)}=84.4$, $p<0.001$) supports this conclusion. We, therefore, reject the alternative hypothesis representing the “completeness logic” (Model 2) in favor of the first-order model representing the “substitutability logic” of EE elements (Model 1). Figure 3 illustrates

Table 2 Comparison of model fit indices

Fit indices	Model 1	Model 2
No. of observations	257	257
No. of parameters	146	112
Chi ²	377.8	462.2
df	279	315
p-value	0.000	0.000
<i>Compared to Model 1</i>		
Chi ² diff		84.4
df diff		36
p-value		0.000
CFI	0.927	0.891
TLI	0.908	0.878
RMSEA	0.037	0.043
90% CI	0.027–0.046	0.034–0.051
CFit	0.991	0.931
SRMR	0.084	0.105

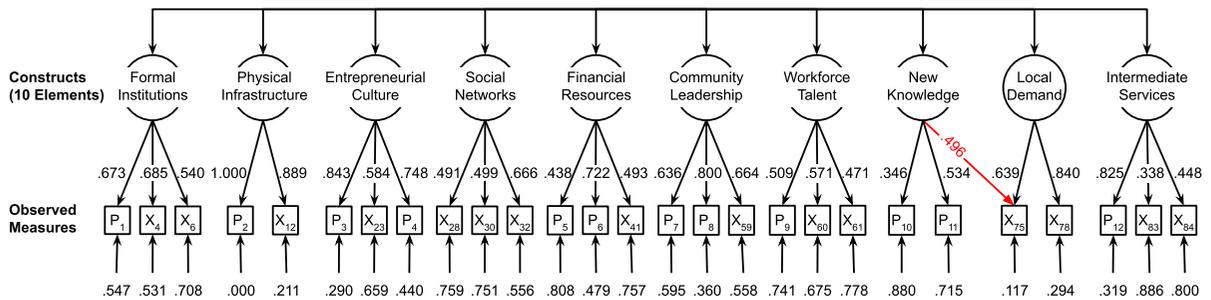
Model 1 represents the first-order CFA, Model 2 the second-order CFA with the EE as the second-order construct. Chi² is evaluated on its p-value ($p<0.05$). Significant values indicate a rejection of the model

the “baseline” first-order model (Model 1), which represents the best-fitting model to the data.

4.2 First-order measurement model

We specified a first-order measurement model with ten EE elements (Stam & Van de Ven, 2021) (see Fig. 3). Despite our best efforts, we could not find three indicators or parcels to reflect the element factors, *physical infrastructure*, *new knowledge*, and *local demand*, and we had to proceed with just two indicators or parcels. However, the element factors become identified when considered within the covariance structure of the overall measurement model. All parameter estimates for our first-order measurement model (Model 1) are reported in Appendix Table 6.

The final measurement model contains one cross-loading from the new knowledge factor to the local demand item “Potential market size in Gross Domestic Product (GDP) per capita in a district” (X75). Standardized residuals and modification indices indicated no further significant points of ill fit in the final solution. However, we note a relatively high factor correlation ($r\geq 0.80$) between physical infrastructure and local demand ($r=0.846$). Nevertheless, standardized factor loadings revealed that most of our indicators/parcels were strongly related to their intended factors



Note. The path diagram reports the fully standardized parameter estimates for the best-fitting first-order measurement model (Model 1). Circles represent unobserved constructs. Rectangles represent measured indicators, e.g., items or parcels of items ('X' for indicators or 'P' for parcels). Single-headed arrows pointing at measured indicators are residual variances. Square double-headed arrows are covariances between factors. Factor covariances were not labeled to avoid clutter but are provided in Appendix A3. The red single-headed arrow indicates one cross-loading between the construct 'new knowledge' and X75. Assumption: P2 is a multifaceted index with less measurement error. Thus, factor loading P2 = 1.000.

Fig. 3 First-order measurement model

(Std. all ≥ 0.50, s). The observed pattern of results and fit indices considerably support our measurement approach to help the EE research program progress.

Finally, we include the indicator “number of innovative startups per district” as the entrepreneurial output variable to proxy productive entrepreneurship. We use this output variable to demonstrate criterion validity for our measurement approach. We correlate the output variable with all ten element constructs of our measurement model and find that all significant coefficients are positive. None of the negative coefficients is either large or statistically significant, which aligns with the EE approach by Stam and Van de Ven (2021). Concerning model fit, we again find “acceptable” values:

RMSEA = 0.044 (90% CI = 0.035–0.052, CFI = 0.883), SRMR = 0.089, CFI = 0.917, and TLI = 0.894 (see Table 8). Table 3 shows the covariance matrix between the entrepreneurial output and the ten EE elements.

Our analysis, focused on the EE Baden-Württemberg, reveals the presence of all ten elements, pointing to the idea of balanced EE configurations by Cavallo et al. (2023). However, elements show varying correlations with the dependent variable, productive entrepreneurship. Our findings resonate with the observations of Zhao et al. (2023) and Leendertse et al. (2022), underscoring the importance of local demand and physical infrastructure, as demonstrated by their high correlations with productive entrepreneurship (see

Table 3 Covariance matrix entrepreneurial output with EE elements

EE output	EE element	Estimate	Std. err	Std. all
Productive entrepreneurship	WITH			
	Formal institutions	0.005	0.004	0.124
	Physical infrastructure	0.034	0.002	0.837***
	Entrepreneurial culture	-0.003	0.003	-0.105
	Social networks	0.003	0.004	-0.091
	Financial resources	0.011	0.003	0.393***
	Community leadership	0.001	0.004	0.014
	Workforce talent	-0.003	0.002	-0.147
	New knowledge	0.009	0.009	0.304
	Local demand	0.030	0.006	0.875***
Intermediate services	-0.003	0.009	-0.076	

p < 0.001 = ***. Productive entrepreneurship—number of innovative startups per district

Table 3). The high correlations infer the relevance of these elements in fostering productive entrepreneurship and may also be reciprocally influenced by productive entrepreneurship. Future EE research can build on these findings and analyze district heterogeneity to detect hidden spatial patterns (i.e., between different urban hotspots or urban and neighboring rural districts) and to better understand the heterogeneity of entrepreneurial activity from a more micro perspective. Furthermore, policymakers can turn to districts as individual geo-political decision-making jurisdictions and leverage policy actions at the district level.

5 Discussion

5.1 Theoretical contribution

The results from our study suggest that more granular data on the founder level using survey instruments and systematic scale development procedures with CFA provide compelling evidence of theoretical constructs' convergent and discriminant validity and advance the EE research program by putting the validity of measurement on a firmer footing. We draw on EE theory (Isenberg, 2010; Stam, 2015; Stam & Van de Ven, 2021; Leendertse et al., 2022; Perugini, 2023) to unpack measurement deficits in current EE research related to (1) the limited data granularity and consistency required by EE theory, (2) the lack of item validation procedures required by measurement theory, and (3) the disconnected nature of EE measures from entrepreneurs. Measurement shortcomings are one reason some theoretical controversies have not yet been resolved satisfactorily. We contribute to three controversial discussions in EE research by developing a new measurement approach.

First, how can we explain the local geographic properties of EEs? Our data shows non-ignorable variation at the district level, and future EE research will benefit from more precise micro-level measures to understand how new venture emergence and growth work for innovative startups in particular contexts. Without such a fine-grained measurement approach, we risk comparing arbitrary numbers of urban districts conflated with arbitrary numbers of rural districts. Consequently, measures are potentially contaminated by critical geographic properties of EEs impacting the heterogeneity of local entrepreneurial activity. An improved understanding of geographic

properties will help to determine more fruitful spatial configurations for particular research questions and policy interventions. Our findings reject the alternative hypothesis of an overarching EE construct in favor of a first-order CFA model. We use undirected correlations among the constructs, which account for the interdependence web of EE elements. Further, our results show varying correlations among all ten EE elements, depicting their interdependencies.

However, our results reveal some limitations in our measurement instrument for local geographic properties. Specifically, we found a high factor covariance between the elements "local demand and physical infrastructure." We note that these factors could not be measured satisfactorily using the survey items included in our study, so we had to rely solely on archival measures with relatively low variance, which may have inflated correlations for these two elements. Although our construct validation procedures rejected self-reported measures for local demand, our results for the constructs based on archival measures are consistent with other studies (Leendertse et al., 2022; Zhao et al., 2023).

Several opportunities to improve the developed metrics deserve attention in future research. In particular, for *physical infrastructure*, survey items about the founders' evaluations of the infrastructure in a district, for example, "In our district, compared to other districts, employees have trouble commuting to work: via public transport/ biking or walking/ by car," and "In our district, compared to other districts, internet speed hinders our business activities/ working from home," should be tested. For *local demand*, other survey items such as "This year/ in three years, we see BW as the primary market for our company," "Number of paying customers this year/ in three years," "Expected market size in millions of euros this year/ in three years," "Expected sales revenues in millions of euros this year/ in three years," and "Expected number of employees this year/ in three years" should be investigated. Furthermore, a noted cross-loading between new knowledge and the local demand item "Potential market size in Gross Domestic Product (GDP) per capita in a district" suggests a shared variance with both EE constructs. By applying our CFA approach, future research can investigate additional measures (both archival and self-reported) to refine the statistical properties of factors and theoretical configurations of elements alike.

Second, how can we measure EEs by combining their micro (self-reported data, bottom-up) and macro

dimensions (archival data, top-down)? In contrast to previous measurement approaches, being either focused on individuals and processes (Corrente et al., 2019; Liguori et al., 2019) or the regional ecosystems (Stam & Van de Ven, 2021; Leendertse et al., 2022; Perugini, 2023; Schrijvers et al., 2024), we argue that synthesizing self-reported and archival measures is beneficial to gain a more comprehensive understanding of the EE phenomenon, especially geographic properties and perceptions of entrepreneurs. We contribute to the emerging discourse about the measurement of EE and EE theory by proposing a new measurement approach at the NUTS-3 level, enhancing the validity of findings from data and facilitating generalization across entrepreneurs, firms, places, and times.

Further, our approach validates and enhances the reliability and validity of existing EE test instruments, addresses controversies regarding EE factor structures and geographic properties, and establishes a process to integrate founders' self-reported survey data with publicly available archival data to capture the ten EE elements. The survey data helps to overcome gaps in archival sources at the micro-level, avoids mixing measures across spatial scales, and involves entrepreneurs in the measurement equation. The relevance of combining both data sources, archival and survey, stems from both theoretical and empirical points of view. We address the theoretical part through two primary approaches: (1) by engaging with measurement theory as outlined in the methods literature (Cook & Campbell, 1979; Little, 2023), and (2) by reinforcing the body of EE literature that positions the entrepreneur as the central actor within the system. The empirical part is the data and EE construct validity evidence that we use to support our application of measurement theory. The NUTS-3 level of analysis adds to the understanding of EEs by giving unique insights into the heterogeneity of entrepreneurial activity and spatial patterns and allowing for observations of activities and mechanisms related to EE actors and participants that would have been ignored using more aggregated data (Audretsch & Belitski, 2021; Bruns et al., 2017).

Third, how can we better understand the relations between entrepreneurs, new ventures, and their local ecosystems? Complementing the work by Leendertse et al. (2022) and expanding the measurement portfolio for EEs to the NUTS-3 level, our district approach allows for more nuanced analyses, facilitates transitioning between multiple levels, and determines the most

appropriate geographic scale for specific research questions in the future. For instance, studying intra-EE relations demands a micro-level (district) analysis, focusing on detailed local interactions (“seeing the trees”), whereas exploring broader, global EE linkages benefits from a more macro-level (regional or state) perspective (“seeing the forest”) (Wurth et al., 2023; Xu et al., 2023). We encourage further empirical research to use our measurement approach to continue “opening the black box of EE.” In particular, future research could explore: (1) the *inclusiveness or exclusiveness* of EEs, for example, examining how local, context-specific inequalities affect different types of productive entrepreneurship—across various social contexts of entrepreneurs (e.g., female entrepreneurs, migrant entrepreneurs), spatial contexts (e.g., urban versus rural district configurations), or industry contexts (e.g., deep tech versus social enterprises)—and how these inequalities impact ecosystem outcomes; (2) the *subjective and objective social ties* in EEs (Billingsley et al., 2023), using the combination of self-reported (subjective) entrepreneur and archival or web-scraped (objective) data.

Finally, our study has some limitations: (1) To replicate and extend our conclusions, the study sample of 257 founders needs to be expanded in size and over time (e.g., Buratti et al., 2023), as an increased number of observations can validate the confidence of our model with “acceptable” fit indices. (2) A convenience sample is not random, and observed respondents are likely to be more similar to each other than unobserved respondents in the population. Therefore, our study's parameter estimates and test statistics will likely include some bias because a convenience sampling strategy can skew estimated coefficients up or down, reduce standard errors, increase test statistics, and reduce *p*-values (Allison, 2009). Because our main concern here is measurement model building as opposed to the statistical testing of substantive hypotheses, potential biases to specific path coefficients are less of a concern. However, future (quantitative) empirical studies building on our approach should use some form of random sampling or a population study strategy (Abootorabi et al., 2021) to test substantive hypotheses grounded in EE theory. By choosing appropriate research designs for future studies, scholars can test hypotheses related to the controversial discussions about the appropriate spatial level of analysis and the multilevel geographic properties of EEs. (3) Our measurement approach focuses on the

ten EE elements of the EE approach by Stam and Van de Ven (2021) to provide a validated set of archival and self-reported measurement items to capture each of the ten EE construct elements. However, there is causal ambiguity between EE and outcome measures that cross-sectional data cannot address. There is no explicit link to outcome variables measuring the economic outcomes, such as the “number of jobs created.” We include the output variable, “number of innovative startups per district,” but only to evaluate criterion validity for our measurement approach. Future research should include both output and outcome variables of the EE approach to assess the antecedents and consequences of the EE phenomenon.

5.2 Policy implications

Despite growing academic interest, EEs are very practitioner-oriented (Colombo et al., 2019). Scholars and policymakers have turned to the strategy of EEs with the explicit goal of it becoming a catalyst for regional economic growth and competitiveness (Audretsch et al., 2021; O’Connor et al., 2018; Stam & Spigel, 2018). However, policy actions to modify EE elements may not always have the intended effects on the outputs (Coad & Srhoj, 2023), as policy interventions are based on aggregated EE evaluations disconnected from entrepreneurs as core actors of the system. We help policymakers monitor interventions that manipulate policy levers related to the EE elements at the NUTS-3 level by (1) using higher-resolution data and (2) capturing entrepreneurs’ values, beliefs, and attitudes.

NUTS territorial units correspond to geo-political decision-making jurisdictions at the state, region, and district levels. Therefore, understanding the multi-level character of EEs is key to effective policymaking, as different EE elements manifest at different spatial levels of aggregation. For example, government subsidies are released at the state or regional level, whereas local culture and local support institutions play out at the district level. NUTS-3 districts have considerable autonomy through self-governance,

and local policies can impact EE elements that translate into entrepreneurial outputs. In practice, the question is about leveraging targeted interventions at the appropriate level of geographic granularity while fostering inclusive EEs for different types of entrepreneurs. Finally, our study addresses the need for precise, actionable insights for entrepreneurs over vague suggestions like “locate in a vibrant EE” or “take advantage of your EE” by developing a measurement approach that integrates entrepreneurs into EE measurement and yields concrete, evidence-based recommendations for entrepreneurs.

6 Conclusion

Despite considerable progress in EE research to understand configurations and causal relations between EE elements and EE outputs, along with different measurement approaches toward EE, the EE literature continues to hold on to aggregated data and measures, disconnected from entrepreneur-specific factors, while lacking systematic scale development procedures to improve the validity and reliability of EE test instruments. Our study proposes a measurement approach for EEs at the NUTS-3 level. We combine civic archival with self-reported entrepreneur data to overcome existing archival data granularity limitations for districts, reduce biases from using a single data source, and enable a more comprehensive perspective on EEs (bottom-up *and* top-down, micro *and* macro). Using systematic scale development, we establish a well-specified measurement model with an acceptable fit to the data and support for the “substitutability logic” of EE elements (Schrijvers et al., 2024; Spigel, 2017; Zhao et al., 2023). Our study is part of an emerging discourse about measuring EEs, and we need further empirical research examining the multilevel nature of ecosystems and their inclusive- or exclusiveness. Understanding the geographic properties of EE is crucial for the multilevel and longitudinal modeling of antecedents and consequences of the EE phenomenon in the future.

Appendix

Table 4 Constitutive definitions: entrepreneurial ecosystem elements

Construct label	Constitutive definition	Source
<i>Entrepreneurial ecosystem</i>		
1. Formal institutions	The extent to which the rule of law is observed in society in a region. Research shows, that for entrepreneurship, the quality and efficiency of (formal) institutions matter and determine, how fruitful policies to promote entrepreneurship can be	(North, 1990; Webb et al., 2020)
2. Physical infrastructure	The extent to which transport and digital infrastructure functions in a region, as infrastructure can enhance regional startup activity, especially broadband, railroads, and highways	(Audretsch et al., 2015)
3. Entrepreneurial culture	The extent to which new venture creation is valued by other people in a region. This social acceptance of entrepreneurship can be considered an informal institution. Regional culture of entrepreneurship (peer effects, norms, and values) can have a long-lasting impact on an entrepreneurship-friendly mindset in a territory	(Fritsch & Wyrwich, 2014)
4. Social networks	The extent to which new ventures are connected for value creation in a region. Networks are building social capital, where entrepreneurs can obtain substantial resources (e.g., information, knowledge, financial capital, and labor)	(Birley, 1985; Malecki, 1997; Stam, 2015)
5. Financial resources	The extent to which founders can access financial resources, e.g., venture capital or public funding in a region. A critical hurdle for starting and scaling new firms is access to capital as a catalyst for commercialization	(Samila & Sorenson, 2010)
6. Community leadership	The extent to which founders take a leadership role in guiding the entrepreneurial ecosystem. At the most fundamental level, studying leadership in regional development is the interest in revealing the things that actors actually (formally and informally) do to influence other actors to work toward a certain goal or shared vision	(Sotarauta et al., 2017; Stam & Van de Ven, 2021)
7. Workforce talent	The extent to which individuals have human capital in either formal education or knowledge, skills, and abilities in a region. It is a crucial input factor for entrepreneurship, fostering new firm formation in a region	(Acs & Armington, 2004; Stam & Van de Ven, 2021)
8. New knowledge	The extent to which investment in new knowledge, skills, and abilities in a region leads to the creation of new business opportunities	(Kim et al., 2012)
9. Local demand	The extent to which there is potential market demand for new products, services, or technologies in a region. For startups, it is important to have a potential regional market, which they can easily access	(Reynolds et al., 1994)
10. Intermediate services	The extent to which intermediate business services are available and accessible in a region. This support can lower barriers for startups to start and grow their business by e.g. reducing search costs	(Zhang & Li, 2010)

Table 5 Descriptive statistics

Var. no	Par. no	Construct	Description	Mean	SD	Min	Max	Skewness	Kurtosis
X3	P1	Formal Institutions	In our district, some people get advantages from their education. ^(*)	5.81	2.21	1	9	-0.45	-0.65
X5	P1	Formal Institutions	In our district, registering property is an obstacle. ^(*)	3.73	2.25	1	9	0.57	-0.55
X4		Formal Institutions	In our district, local regulations are an obstacle to starting our business. ^(*)	3.98	2.45	1	9	0.41	-1.05
X6		Formal Institutions	In our district, tax rates slow down business growth. ^(*)	4.30	2.39	1	9	0.35	-0.88
X9	P2	Physical Infrastructure	Population accessible within 1h30 by road in a district, as share of the population within a 120 km radius. ^(****)	89.19	10.70	53.16	106	-0.78	0.89
X10	P2	Physical Infrastructure	Population accessible within 1h30 by rail in a district, as share of the population within a 120 km radius, combined w. short walk. ^(****)	17.47	7.32	1.38	23.28	-0.70	-1.11
X11	P2	Physical Infrastructure	Population accessible within 1h30 by rail in a district, as share of the population within a 120 km radius., combined w. short bike ride. ^(****)	31.38	11.13	3.32	48.90	-0.70	-0.39
X12		Physical Infrastructure	Highest speed of broadband connection available by local administrative unit in a district. ^(****)	98.78	13.43	49.59	113.45	-1.39	1.36
X14	P3	Entrepreneurial Culture	We are building a startup to take advantage of the business opportunity. ^(*)	6.84	1.90	1	9	-1.19	1.29
X17	P3	Entrepreneurial Culture	We are building a startup because we search for independence. ^(*)	7.32	1.82	1	9	-1.31	1.50
X21	P3	Entrepreneurial Culture	The entrepreneurial culture in our district supports individual success. ^(*)	5.27	1.67	1	9	0	-0.62
X25	P3	Entrepreneurial Culture	The entrepreneurial culture in our district supports individual way of life. ^(*)	5.02	1.81	1	9	-0.21	-0.42
X23		Entrepreneurial Culture	The entrepreneurial culture in our district encourages risk taking. ^(*)	4.33	2.09	1	9	0	-1.04
X18	P4	Entrepreneurial Culture	We are building a startup to increase personal income. ^(*)	5.06	1.67	1	9	-0.11	-1.17

Table 5 (continued)

Var. no	Par. no	Construct	Description	Mean	SD	Min	Max	Skewness	Kurtosis
X24	P4	Entrepreneurial Culture	The entrepreneurial culture in our district encourages creativity. ^(*)	5.29	1.91	1	9	-0.28	-0.83
X28		Social Networks	Ties to other firms for collaboration. (e.g., SMEs). ^(****)	6.58	5.95	1	25	1.65	2.25
X30		Social Networks	Ties to other startup founders for collaboration. ^(****)	4.36	3.86	1	15	1.69	1.88
X32		Social Networks	Ties to entrepreneurial support organizations, providing resources to develop the business (e.g., knowledge, money). ^(****)	24.09	28.48	1	100	1.82	2.18
X35	P5	Financial Resources	We access professional funding. ^(**)	0.36	0.48	0	1.00	0.58	-1.67
X40	P5	Financial Resources	In our district, there is sufficient debt funding available. ^(*)	4.47	2.04	1.00	9.00	0.01	-0.98
X37	P6	Financial Resources	We access public funding. ^(**)	0.65	0.48	0	1.00	-0.61	-1.64
X39	P6	Financial Resources	In our district, there is sufficient equity funding available. ^(*)	4.68	2.10	1.00	9.00	0.11	-0.66
X42	P6	Financial Resources	In our district, there is sufficient funding from informal investors available. ^(*)	5.11	1.67	1.00	9.00	-0.26	0.21
X43	P6	Financial Resources	Value of government subsidies per district (EUR). ^(***)	68,820	35,848	3,647	104,980	-0.50	-1.51
X41		Financial Resources	In our district, there are sufficient government subsidies available. ^(*)	5.19	2.26	1.00	9.00	0.03	-1.05
X55	P7	Community Leadership	We take actions that go beyond firm-level activities. ^(*)	5.25	2.10	1.00	9.00	-0.15	-0.52
X56	P7	Community Leadership	We regularly attend startup events in our district. ^(*)	5.90	2.40	1.00	9.00	-0.55	-0.80
X57	P8	Community Leadership	We collaborate with other founders to guide regional development. ^(*)	4.99	2.27	1.00	9.00	-0.12	-1.07
X58	P8	Community Leadership	We provide other actors with a vision to work toward. ^(*)	6.03	2.31	1.00	9.00	-0.54	-0.71
X59		Community Leadership	Our activities contribute to higher recognition of entrepreneurial activities among policymakers. ^(*)	5.21	2.16	1.00	9.00	-0.22	-0.73
X60		Workforce Talent	Developing new ideas is important to us. ^(*)	8.17	1.06	3	9	-1.42	3.06
X61		Workforce Talent	Doing things on our own is important to us. ^(*)	7.76	1.40	3	9	-1.12	0.93

Table 5 (continued)

Var. no	Par. no	Construct	Description	Mean	SD	Min	Max	Skewness	Kurtosis
X62	P9	Workforce Talent	Being creative is important to us. ^(*)	7.89	1.44	1.00	9.00	-1.73	3.95
X63	P9	Workforce Talent	I have founded another startup before. ^(**)	0.43	0.50	0	1.00	0.28	-1.93
X67	P9	Workforce Talent	Number of people per district that completed tertiary education. ^(***)	7,142	2,399	1,460	10,010	-0.70	-0.94
X70	P10	New Knowledge	We have published peer-reviewed articles. ^(**)	0.23	0.42	0	1.00	1.30	-0.32
X72	P10	New Knowledge	Number of research centers per district. ^(***)	7.93	4.59	1.00	12.00	-0.35	-1.69
X69	P11	New Knowledge	We have applied for patents. ^(**)	0.24	0.43	0	1.00	1.21	-0.53
X73	P11	New Knowledge	Value of R&D expenditure per district (EUR in bn). ^(***)	2.45	2.05	0.06	4.59	0.04	-1.93
X75		Local Demand	Potential market size in Gross Domestic Product (GDP) per capita in a district. ^(****)	69,396	22,003	29,653	91,228	-0.33	-1.48
X78		Local Demand	Number of unemployed individuals in a district. ^(***)	12,695	5,727	2,683	18,616	-0.18	-1.56
X81	P12	Intermediate Services	We have participated in multiple accelerator/incubator programs. ^(**)	0.84	0.37	0	1.00	-1.82	1.31
X82	P12	Intermediate Services	We receive support from an external consulting firm. ^(**)	0.23	0.42	0	1.00	1.30	-0.31
X83		Intermediate Services	We believe that being part of accelerator/incubator programs helped us to reach our goals faster. ^(*)	6.83	1.79	1.00	9.00	-0.82	0.31
X84		Intermediate Services	We are using external offices, labs, maker-spaces, mentors, coaches, university facilities to develop our business. ^(**)	0.86	0.35	0	1.00	-2.04	2.19
O1		Productive Entrepreneurship	Number of innovative startups per district. ^(***)	352.45	231.02	18.00	594.00	-0.09	-1.74

Note. The 45 indicators used in the analysis are displayed (X_n). O_1 is the output variable used for criterion validity. A total of 30 indicators were parceled into 12 parcels (P_n). ^(*): 9-point scale: agree-disagree, standardized 0–1; ^(**): binary (y,n); ^(***): district-sensitive items adjusted for NUTS-3 district population density, standardized 0–1; ^(****): non-district-sensitive items, standardized 0–1. Descriptives are reported before adjusting district-sensitive indicators for NUTS-3 population density and standardization (0–1). Referring to guidelines by (Kline, 2016), values for skewness should not exceed >|3| and for kurtosis >|10| when univariate distributions are normal. Dichotomous variable scales were coded as follows: 1 = “yes”; 0 = “no”

Table 6 Selected results measurement model, CFA model first-order

Var. no	Par. no	Construct	Estimate	Std. err	Std. all
Latent Variables					
X3, X5	P1	Formal Institutions	0.860	0.129	0.673***
X4		Formal Institutions	1.209	0.143	0.685***
X6		Formal Institutions	0.931	0.168	0.540***
X9, X10, X11	P2	Physical Infrastructure	1.324	0.021	1.000***
X12		Physical Infrastructure	0.676	0.021	0.889***
X14, X17, X21, X25	P3	Entrepreneurial Culture	0.871	0.098	0.843***
X23		Entrepreneurial Culture	1.058	0.088	0.584***
X18, X24	P4	Entrepreneurial Culture	1.072	0.100	0.748***
X28		Social Networks	0.806	0.329	0.491*
X30		Social Networks	0.889	0.330	0.499**
X32		Social Networks	1.305	0.288	0.666***
X35, X40	P5	Financial Resources	0.935	0.179	0.438***
X37, X39, X42, X43	P6	Financial Resources	1.007	0.283	0.722***
X41		Financial Resources	1.058	0.302	0.493***
X55, X56	P7	Community Leadership	0.849	0.102	0.636***
X57, X58	P8	Community Leadership	1.122	0.119	0.800***
X59		Community Leadership	1.029	0.104	0.664***
X62, X63, X67	P9	Workforce Talent	1.181	0.302	0.509***
X60		Workforce Talent	0.873	0.152	0.571***
X61		Workforce Talent	0.946	0.268	0.471***
X70, X72	P10	New Knowledge	0.748	0.289	0.346*
X69, X73	P11	New Knowledge	1.194	0.228	0.534***
X75		Local Demand	1.245	0.085	0.639***
X78		Local Demand	0.755	0.085	0.840***
X81, X82	P12	Intermediate Services	1.564	0.652	0.825*
X83		Intermediate Services	0.433	0.217	0.338***
X84		Intermediate Services	1.003	0.552	0.448(*)
Construct		Construct	Estimate	Std. Err	Std. All
Covariances					
Formal Institutions		WITH			
		Physical Infrastructure	0.004	0.002	0.149
		Entrepreneurial Culture	0.000	0.003	0.004
		Social Networks	-0.003	0.003	-0.149
		Financial Resources	-0.005	0.004	-0.281
		Community Leadership	0.003	0.003	0.115
		Workforce Talent	0.003	0.002	0.252
		New Knowledge	0.006	0.003	0.335*
		Local Demand	0.003	0.003	0.163
		Intermediate Services	-0.001	0.004	-0.029
Physical Infrastructure		WITH			
		Entrepreneurial Culture	-0.002	0.002	-0.118
		Social Networks	0.003	0.003	0.123
		Financial Resources	0.005	0.002	0.265*
		Community Leadership	-0.001	0.002	-0.024
		Workforce Talent	-0.002	0.001	-0.128

Table 6 (continued)

Var. No	Par. No	Construct	Estimate	Std. Err	Std. All
		New Knowledge	0.008	0.002	0.434***
		Local Demand	0.016	0.002	0.846***
		Intermediate Services	0.001	0.005	-0.059
Entrepreneurial Culture		WITH			
		Social Networks	-0.004	0.003	-0.244(*)
		Financial Resources	0.003	0.004	0.202
		Community Leadership	0.000	0.002	0.014
		Workforce Talent	-0.000	0.002	-0.012
		New Knowledge	-0.005	0.002	-0.324*
		Local Demand	-0.000	0.002	-0.031
		Intermediate Services	0.001	0.003	0.048
Social Networks		WITH			
		Financial Resources	0.004	0.003	0.227
		Community Leadership	0.009	0.003	0.412***
		Workforce Talent	0.002	0.003	0.145
		New Knowledge	-0.001	0.003	-0.032
		Local Demand	0.001	0.002	0.047
		Intermediate Services	0.003	0.006	0.112
Financial Resources		WITH			
		Community Leadership	0.004	0.003	0.228
		Workforce Talent	-0.003	0.002	-0.376
		New Knowledge	0.001	0.003	0.048
		Local Demand	-0.000	0.002	-0.014
		Intermediate Services	0.010	0.003	0.552***
Community Leadership		WITH			
		Workforce Talent	0.005	0.002	0.382*
		New Knowledge	0.000	0.002	0.019
		Local Demand	-0.002	0.002	-0.119
		Intermediate Services	0.008	0.006	0.348
Workforce Talent		WITH			
		New Knowledge	-0.001	0.002	-0.073
		Local Demand	-0.001	0.001	-0.114
		Intermediate Services	-0.001	0.003	-0.054
New Knowledge		WITH			
		Local Demand	0.005	0.003	0.360*
		Intermediate Services	0.001	0.004	0.078
Local Demand		WITH			
		Intermediate Services	-0.006	0.004	-0.291
Var. No	Par. No	Construct	Estimate	Std. Err	Std. All
Variances					
X3, X5	P1	Formal Institutions	0.021	0.004	0.547***
X4		Formal Institutions	0.039	0.010	0.531***
X6		Formal Institutions	0.049	0.010	0.708***
X9, X10, X11	P2	Physical Infrastructure	0.000		0.000
X12		Physical Infrastructure	0.003	0.000	0.211***
X14, X17, X21, X25	P3	Entrepreneurial Culture	0.005	0.002	0.290*
X23		Entrepreneurial Culture	0.035	0.005	0.659***

Table 6 (continued)

X18, X24	P4	Entrepreneurial Culture	0.015	0.004	0.440***
X28		Social Networks	0.042	0.013	0.759***
X30		Social Networks	0.049	0.013	0.751***
X32		Social Networks	0.044	0.017	0.556***
X35, X40	P5	Financial Resources	0.050	0.006	0.808***
X37, X39, X42, X43	P6	Financial Resources	0.013	0.006	0.479*
X41		Financial Resources	0.048	0.010	0.757***
X55, X56	P7	Community Leadership	0.026	0.005	0.595***
X57, X58	P8	Community Leadership	0.017	0.006	0.360***
X59		Community Leadership	0.032	0.006	0.558***
X62, X63, X67	P9	Workforce Talent	0.024	0.005	0.741***
X60		Workforce Talent	0.009	0.003	0.674***
X61		Workforce Talent	0.019	0.004	0.778***
X70, X72	P10	New Knowledge	0.052	0.008	0.880***
X69, X73	P11	New Knowledge	0.046	0.007	0.715***
X75		Local Demand	0.007	0.005	0.117
X78		Local Demand	0.004	0.001	0.294***
X81, X82	P12	Intermediate Services	0.028	0.053	0.319
X83		Intermediate Services	0.035	0.006	0.886***
X84		Intermediate Services	0.097	0.025	0.800***

Note. $p < 0.001 = ***$; $p < 0.01 = **$; $p < 0.05 = *$; $p < 0.1 = (*)$. Assumption: P2 is a multifaceted index with less measurement error. Thus, Std. all P2=1.000 and residual variance P2=0.000. Factor loadings from factor variances=1.000*** and are not explicitly listed.

Table 7 Selected results measurement model, CFA model second-order

Var. No	Par. No	Construct	Estimate	Std. Err	Std. All
Latent Variables					
X3, X5	P1	Formal Institutions	0.834	0.114	0.655***
X4		Formal Institutions	1.209	0.156	0.735***
X6		Formal Institutions	0.875	0.138	0.510***
X9, X10, X11	P2	Physical Infrastructure	1.324	0.021	1.000***
X12		Physical Infrastructure	0.676	0.021	0.889***
X14, X17, X21, X25	P3	Entrepreneurial Culture	0.935	0.103	0.892***
X23		Entrepreneurial Culture	1.028	0.086	0.559***
X18, X24	P4	Entrepreneurial Culture	1.037	0.091	0.712***
X28		Social Networks	0.990	0.378	0.599**
X30		Social Networks	0.911	0.392	0.510*
X32		Social Networks	1.099	0.395	0.557**
X35, X40	P5	Financial Resources	0.764	0.385	0.338*
X37, X39, X42, X43	P6	Financial Resources	1.322	0.745	0.903(*)
X41		Financial Resources	0.914	0.410	0.402*
X55, X56	P7	Community Leadership	0.798	0.089	0.594***
X57, X58	P8	Community Leadership	1.213	0.130	0.861***
X59		Community Leadership	0.988	0.108	0.634***
X62, X63, X67	P9	Workforce Talent	1.141	0.219	0.483***
X60		Workforce Talent	1.038	0.244	0.668***
X61		Workforce Talent	0.821	0.197	0.403***
X70, X72	P10	New Knowledge	0.604	0.353	0.265(*)
X69, X73	P11	New Knowledge	1.047	0.562	0.444(*)
X75		Local Demand	1.133	0.440	0.488*
X78		Local Demand	0.867	0.440	0.808*
X81, X82	P12	Intermediate Services	1.198	0.369	0.566**
X83		Intermediate Services	0.793	0.498	0.524
X84		Intermediate Services	1.008	0.369	0.384**
Construct		Construct	Estimate	Std. Err	Std. All
Covariances					
Entrepreneurial Ecosystem		WITH			
		Formal Institutions	1.087	0.492	0.212*
		Physical Infrastructure	4.581	0.786	0.886***
		Entrepreneurial Culture	-0.658	0.466	-0.157
		Social Networks	0.462	0.591	0.097
		Financial Resources	0.707	0.358	0.193*
		Community Leadership	-0.293	0.552	-0.057
		Workforce Talent	-0.429	0.325	-0.170
		New Knowledge	2.161	1.471	0.606
		Local Demand	3.451	1.686	1.000*
		Intermediate Services	-1.069	0.785	-0.242
Var. No	Par. No	Construct	Estimate	Std. Err	Std. All
Variances					
X3, X5	P1	Formal Institutions	0.022	0.004	0.571***
X4		Formal Institutions	0.034	0.011	0.460**
X6		Formal Institutions	0.052	0.009	0.740***

Table 7 (continued)

X9, X10, X11	P2	Physical Infrastructure	0.000		0.000
X12		Physical Infrastructure	0.003	0.000	0.211***
X14, X17, X21, X25	P3	Entrepreneurial Culture	0.004	0.002	0.205
X23		Entrepreneurial Culture	0.037	0.005	0.688***
X18, X24	P4	Entrepreneurial Culture	0.017	0.004	0.493***
X28		Social Networks	0.036	0.016	0.641*
X30		Social Networks	0.048	0.015	0.740**
X32		Social Networks	0.055	0.019	0.690**
X35, X40	P5	Financial Resources	0.055	0.009	0.886***
X37, X39, X42, X43	P6	Financial Resources	0.005	0.019	0.185
X41		Financial Resources	0.052	0.011	0.838***
X55, X56	P7	Community Leadership	0.028	0.005	0.648***
X57, X58	P8	Community Leadership	0.012	0.007	0.259(*)
X59		Community Leadership	0.034	0.006	0.599***
X62, X63, X67	P9	Workforce Talent	0.024	0.003	0.766***
X60		Workforce Talent	0.008	0.003	0.553*
X61		Workforce Talent	0.020	0.004	0.838***
X70, X72	P10	New Knowledge	0.055	0.007	0.930***
X69, X73	P11	New Knowledge	0.051	0.010	0.803***
X75		Local Demand	0.003	0.015	0.048
X78		Local Demand	0.004	0.001	0.347***
X81, X82	P12	Intermediate Services	0.054	0.023	0.680*
X83		Intermediate Services	0.029	0.010	0.725**
X84		Intermediate Services	0.103	0.024	0.852***

Note. $p < 0.001 = ***$; $p < 0.01 = **$; $p < 0.05 = *$; $p < 0.1 = (*)$. Assumption: P2 is a multifaceted index with less measurement error. Thus, Std. all P2=1.000 and residual variance P2=0.000. Factor loadings from factor variances = 1.000*** and are not explicitly listed.

Table 8 Selected results, SEM with entrepreneurial output

Var. No	Par. No	Construct	Estimate	Std. Err	Std. All
Latent Variables					
X3, X5	P1	Formal Institutions	0.853	0.157	0.668***
X4		Formal Institutions	1.227	0.162	0.696***
X6		Formal Institutions	0.920	0.162	0.534***
X9, X10, X11	P2	Physical Infrastructure	1.324	0.021	1.000***
X12		Physical Infrastructure	0.676	0.021	0.889***
X14, X17, X21, X25	P3	Entrepreneurial Culture	0.895	0.104	0.861***
X23		Entrepreneurial Culture	1.046	0.087	0.572***
X18, X24	P4	Entrepreneurial Culture	1.059	0.100	0.734***
X28		Social Networks	0.828	0.365	0.505*
X30		Social Networks	0.908	0.379	0.511*
X32		Social Networks	1.265	0.382	0.647**
X35, X40	P5	Financial Resources	0.778	0.183	0.347***
X37, X39, X42, X43	P6	Financial Resources	1.339	0.283	0.907***
X41		Financial Resources	0.882	0.216	0.391***
X55, X56	P7	Community Leadership	0.848	0.108	0.634***
X57, X58	P8	Community Leadership	1.143	0.124	0.814***
X59		Community Leadership	1.009	0.103	0.651***
X62, X63, X67	P9	Workforce Talent	1.152	0.287	0.495***
X60		Workforce Talent	0.889	0.170	0.580***
X61		Workforce Talent	0.959	0.272	0.476***
X70, X72	P10	New Knowledge	0.597	0.426	0.267
X69, X73	P11	New Knowledge	1.433	0.759	0.618(*)
X75		Local Demand	1.298	0.129	0.701***
X78		Local Demand	0.702	0.129	0.821***
X81, X82	P12	Intermediate Services	1.627	0.753	0.862*
X83		Intermediate Services	0.425	0.220	0.333(*)
X84		Intermediate Services	0.948	0.623	0.424
Construct		Construct	Estimate	Std. Err	Std. All
Covariances					
Productive Entrepreneurship		WITH			
		Formal Institutions	0.005	0.004	0.124
		Physical Infrastructure	0.034	0.002	0.837***
		Entrepreneurial Culture	-0.003	0.003	-0.105
		Social Networks	0.003	0.004	-0.091
		Financial Resources	0.011	0.003	0.393***
		Community Leadership	0.001	0.004	0.014
		Workforce Talent	-0.003	0.002	-0.147
		New Knowledge	0.009	0.009	0.304
		Local Demand	0.030	0.006	0.875***
		Intermediate Services	-0.003	0.009	-0.076
Var. No	Par. No	Construct	Estimate	Std. Err	Std. All
Variances					
X3, X5	P1	Formal Institutions	0.021	0.005	0.553***
X4		Formal Institutions	0.038	0.011	0.516**
X6		Formal Institutions	0.050	0.010	0.715***

Table 8 (continued)

X9, X10, X11	P2	Physical Infrastructure	0.000		0.000
X12		Physical Infrastructure	0.003	0.000	0.211***
X14, X17, X21, X25	P3	Entrepreneurial Culture	0.005	0.002	0.259(*)
X23		Entrepreneurial Culture	0.036	0.005	0.672***
X18, X24	P4	Entrepreneurial Culture	0.015	0.004	0.462***
X28		Social Networks	0.042	0.014	0.745**
X30		Social Networks	0.049	0.015	0.739**
X32		Social Networks	0.046	0.021	0.582**
X35, X40	P5	Financial Resources	0.055	0.006	0.879***
X37, X39, X42, X43	P6	Financial Resources	0.005	0.007	0.177
X41		Financial Resources	0.053	0.006	0.847***
X55, X56	P7	Community Leadership	0.026	0.005	0.598***
X57, X58	P8	Community Leadership	0.016	0.006	0.337**
X59		Community Leadership	0.033	0.006	0.557***
X62, X63, X67	P9	Workforce Talent	0.024	0.004	0.755***
X60		Workforce Talent	0.009	0.003	0.663**
X61		Workforce Talent	0.018	0.004	0.773***
X70, X72	P10	New Knowledge	0.055	0.009	0.929***
X69, X73	P11	New Knowledge	0.040	0.021	0.618(*)
X75		Local Demand	0.007	0.007	0.125
X78		Local Demand	0.004	0.001	0.325***
X81, X82	P12	Intermediate Services	0.022	0.065	0.256
X83		Intermediate Services	0.035	0.006	0.889***
X84		Intermediate Services	0.100	0.027	0.821***

Note. $p < 0.001 = ***$; $p < 0.01 = **$; $p < 0.05 = *$; $p < 0.1 = (*)$. Assumption: P2 is a multifaceted index with less measurement error. Thus, Std. all P2=1.000 and residual variance P2=0.000. Factor loadings from factor variances = 1.000*** and are not explicitly listed.

Table 9 Tested Items as Indicators for Entrepreneurial Ecosystem Elements

Construct	Measurement description
Formal institutions	In our district, some founders get advantages from their access to local politicians
Formal institutions	In our district, some founders get advantages from their industry contacts
Formal institutions	In our district, some people get advantages from their education
Formal institutions	In our district, local regulations are an obstacle to starting a business
Formal institutions	In our district, registering property is an obstacle
Formal institutions	In our district, tax rates slow down business growth
Formal institutions	In our district, loans are easy to come by
Formal institutions	In our district, loans are easy to come by
Formal institutions	Trade tax per capita in a district. [x]
Physical Infrastructure	Population accessible within 1h30 by road in a district, as share of the population within a 120 km radius. [x]
Physical Infrastructure	Population accessible within 1h30 by rail in a district, as share of the population within a 120 km radius, combined with short walk. [x]
Physical Infrastructure	Population accessible within 1h30 by rail in a district, as share of the population within a 120 km radius., combined with short bike ride. [x]
Physical Infrastructure	Highest speed of broadband connection available by local administrative unit in a district. [x]
Physical Infrastructure	Daily number of passenger flights accessible in 90 min drive. [x]
Entrepreneurship Culture	We are building a startup because we want to maintain our income level
Entrepreneurship Culture	We are building a startup because we search for opportunities
Entrepreneurship Culture	We are building a startup because we have no better choices for work
Entrepreneurship Culture	We are building a startup to take advantage of the business opportunity
Entrepreneurship Culture	We are building a startup because we search for independence
Entrepreneurship Culture	We are building a startup to increase personal income
Entrepreneurship Culture	We are building a startup due to a combination of the above mentioned factors
Entrepreneurship Culture	The entrepreneurial culture in our district encourages creativity
Entrepreneurship Culture	The entrepreneurial culture in our district supports individual way of life
Entrepreneurship Culture	The entrepreneurial culture in our district encourages risk taking
Entrepreneurship Culture	The entrepreneurial culture in our district supports individual success
Entrepreneurship Culture	The entrepreneurial culture in our district supports individual initiatives
Entrepreneurship Culture	Number of new firms per capita in a district. [x]
Social Networks	Ties to other firms for collaboration (e.g., SMEs)
Social Networks	Ties to other startup founders for collaboration
Social Networks	Ties to entrepreneurial support organizations, providing resources to develop the business (e.g., knowledge, money)
Social Networks	Number of publicly funded ecosystem support organizations per district. [x]
Social Networks	Number of ecosystem support organizations in Baden-Württemberg. [x]
Social Networks	Number of ecosystem actors actively involved in supporting the business per startup
Social Networks	In our district, it was easy to find a space to carry out our work
Financial Resources	We access professional funding
Financial Resources	We access public funding
Financial Resources	In our district, there is sufficient equity funding available
Financial Resources	In our district, there is sufficient debt funding available
Financial Resources	In our district, there are sufficient government subsidies available
Financial Resources	In our district, there is sufficient funding from informal investors available
Financial Resources	Value of government subsidies per district (EUR). [x]
Financial Resources	We have completed our first sales

Table 9 (continued)

Construct	Measurement description
Financial Resources	Number of investors invested per startup
Financial Resources	Number of Business Angel Networks in a district. [x]
Financial Resources	In our district, there are sufficient crowdfunding opportunities
Financial Resources	In our district, there are sufficient IPO opportunities
Financial Resources	In our district, there is sufficient venture capital funding available
Financial Resources	In our district, there is sufficient Business Angel funding available
Financial Resources	Number of funding sources actively involved in startups
Leadership	I have taken leadership courses to develop my leadership skills
Leadership	I have a leadership position in voluntary work
Leadership	I have certified project management skills
Leadership	I have an MBA
Leadership	I have worked in a company before
Leadership	We take actions that go beyond firm-level activities
Leadership	We regularly attend startup events in our district
Leadership	We collaborate with other founders to guide regional development
Leadership	We provide other actors with a vision to work toward
Leadership	Our activities contribute to higher recognition of entrepreneurial activities among policymakers
Workforce Talent	I have founded another startup before
Workforce Talent	Share of total population per district that completed tertiary education. [x]
Workforce Talent	Developing new ideas is important to us
Workforce Talent	Being creative is important to us
Workforce Talent	Doing things on our own is important to us
Workforce Talent	I have exited another startup before
Workforce Talent	Mean work experience of startup founders
Workforce Talent	I have participated in entrepreneurship education
New Knowledge	We have applied for patents
New Knowledge	We have registered patents
New Knowledge	Value of R&D expenditure per district (EUR in bn). [x]
New Knowledge	Number of research centers per district. [x]
New Knowledge	We have published peer-reviewed articles
New Knowledge	We consider our startup as an emerging technology startup
New Knowledge	Number of excellence clusters at universities in a district. [x]
Local Demand	Share of unemployed individuals in a district. [x]
Local Demand	Potential market size in Gross Domestic Product (GDP) per capita in a district. [x]
Local Demand	We have active customers that buy our product, technology, services
Local Demand	Unemployment rate (in%) per district. [x]
Local Demand	Disposable income per capita in a district. [x]
Intermediate Services	We believe that being part of accelerator/incubator programs helped us to reach our goals faster
Intermediate Services	We receive support from an external consulting firm
Intermediate Services	We are using external offices, labs, makerspaces, mentors, coaches, university facilities to develop our business
Intermediate Services	We have participated in multiple accelerator/incubator programs
Intermediate Services	Number of active accelerator/incubator participations per startup
Intermediate Services	Number of accelerators/incubators in a district. [x]

Note. [x] = items based on archival data; all other items are based on survey data

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Declarations

Conflict of interest The authors declare no competing interests.

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