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Entrepreneurial Ecosystem Metrics

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Abstract
In spite of the popularity of the entrepreneurial ecosystem approach in science and policy, there is a scarcity of credible, accurate and comparable metrics of entrepreneurial ecosystems. This is a severe shortcoming for both scientific progress and successful policy. In this paper, we bridge this metrics gap. We use the entrepreneurial ecosystem approach to quantify and qualify regional economies. Entrepreneurial ecosystems consist of the actors and factors that enable entrepreneurship. We operationalize the elements and outputs of entrepreneurial ecosystems for 273 European regions. The ecosystem elements show strong and positive correlations between them, confirming the systemic nature of entrepreneurial economies, and the need for a complex systems perspective. Our analyses show that physical infrastructure, finance, formal institutions, and talent take a central position in the interdependence web, providing a first indication of these elements as fundamental conditions of entrepreneurial ecosystems. The measures of the elements are used to calculate an index to approximate the quality of entrepreneurial ecosystems. This index is robust and performs well in regressions to predict entrepreneurial output, which we measure with novel data on productive entrepreneurship. The entrepreneurial ecosystem approach and the metrics we present provide a lens for public policy to better diagnose, understand and improve entrepreneurial economies.

Keywords: entrepreneurial ecosystem; regional dynamics; entrepreneurship; economic development; economic policy; entrepreneurship policy

JEL classification: D2, E02, L26, M13, O43, P00, R1, R58

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1. Introduction

Even though the academic literature on entrepreneurial ecosystems has been flourishing recently, it does not yet provide an actionable framework for economic policy. An important reason for this absence is the scarcity of credible, accurate and especially comparable metrics of entrepreneurial ecosystems. An entrepreneurial ecosystem comprises a set of interdependent actors and factors that are governed in such a way that they enable productive entrepreneurship within a particular territory (Stam, 2015; Stam and Spigel, 2018). The entrepreneurial ecosystem approach has become popular due to the gradual shift in economic policy from managerial economies to entrepreneurial economies (Thurik et al., 2013). In these entrepreneurial economies entrepreneurship is considered a key driver of economic change (Schumpeter, 1934).

The entrepreneurial ecosystem approach offers a lens to empirically trace the systemness of entrepreneurial economies and the degree to which economic systems produce entrepreneurship, as an emergent property of the system (Brown and Mason, 2014; Isenberg, 2010; Stam, 2015). It is especially useful to synthesize and integrate a large variety and quantity of data to measure the (changing) nature, outputs and outcomes of (regional) economies (Stam, 2015). The entrepreneurial ecosystem approach thus has the potential to provide an actionable framework that guides policymaking.

However, the lack of sufficient metrics on entrepreneurial ecosystems makes it difficult to have adequate diagnosis and monitoring in the policy cycle. The lack of adequate diagnosis and monitoring is one of the reasons that economic policy often fails to achieve its objectives. In this paper we address the metrics gap by developing and applying entrepreneurial ecosystem metrics to analyse entrepreneurial economies. These metrics enable adequate diagnosis of entrepreneurial economies and allow for the monitoring of economic change generated by policy and other dynamics. This paper thus takes heed of the old carpenter's adage "measure twice, cut once", by reducing policy failures with better measurement tools.

While the entrepreneurial ecosystem approach has become very prominent over the last decade, it still lacks much empirical evidence. The existing empirical studies are often qualitative case studies, such as those by Spigel (2017) in Canada and Mack and Mayer (2016) in the US. There are earlier attempts to measure entrepreneurial ecosystems with quantitative data, such as the study by Ács et al. (2014). However, these studies focus on the national level (Ács et al., 2014; Radosevic and Yoruk, 2013). In this study we instead focus on the regional level, because entrepreneurship is largely a regional event (Feldman, 2001), and there is substantial variation in entrepreneurship between regions within countries. The level of the (city-)region is generally seen as the more adequate level from a policy (Katz and Bradly, 2013; Spigel, 2020) and entrepreneurship practice (Feld, 2012; Feldman, 2001) point of view. This study will be the first to create a harmonized dataset to measure entrepreneurial ecosystems at the regional level in a large set of countries.

Developing entrepreneurial ecosystem metrics encompasses quantification and qualification. Quantification involves measuring the key elements with a wide range of data sources (Credit et al., 2018). Qualification involves developing a methodology that provides insight into the extent to which these elements are interdependent, into the overall quality of the entrepreneurial economy, and how this relates to entrepreneurial outputs. We have three main research questions. First and foremost, how can we compose a harmonized data set with which the quality of key elements of entrepreneurial economies can be measured? We develop a universal set of constructs for each entrepreneurial ecosystem element and we source data from a large variety of datasets to compose credible, accurate, and especially comparable metrics of entrepreneurial ecosystems. We measure entrepreneurial ecosystems with a harmonized dataset in the context of 273 regions in 28 European countries. Europe provides an excellent laboratory for analysing entrepreneurial economies because it contains a large number of regions that exhibit striking variation in socio-economic conditions, entrepreneurial activity, and economic growth.

Second, to what extent and how are the elements of entrepreneurial economies interdependent? Interdependence is a key aspect of complex systems (Aghion et al., 2009; Simon, 1962). Studying if there are strong interdependencies between the elements thus helps answer the question whether entrepreneurial economies can be seen as complex systems. We show with multiple statistical methods to what extent and how the elements of entrepreneurial economies are interdependent. Third, how can we determine the quality of entrepreneurial economies? We will answer this question with a synthesis of our entrepreneurial ecosystem element metrics into an entrepreneurial ecosystem index and analyse its relation to entrepreneurial outputs. Entrepreneurial output is an indicator of the emergent property of entrepreneurial economies. We use multiple data sources and metrics to determine entrepreneurial outputs at the regional level. Using novel methods, including web scraping and geocoding, we determine the entrepreneurial outputs in the form of the number of (Crunchbase listed) innovative new firms and unicorns - young private firms with a valuation of more than $1 billion - per region.

The outline of our paper is as follows. First, we discuss the key mechanisms that explain the prevalence of entrepreneurship and economic development. Second, we discuss and develop the measures that are needed to approximate the key elements of entrepreneurial economies. These measures allow us to quantify the elements and to qualify entrepreneurial economies. Third, we relate the developed metrics to entrepreneurial outputs. The final sections conclude, reflect on the findings, policy implications, and set out an agenda for further research.

2. Entrepreneurship and economic development

In this section we discuss the state of the art of empirical research on the (inter)relation between entrepreneurship and (regional) economic development, synthesize this into an entrepreneurial ecosystem framework, and advance our understanding of entrepreneurial ecosystems with a complex systems perspective. The empirical literature on entrepreneurship and (regional) economic development can be divided in the entrepreneurship growth literature, focusing on the aggregate economic effects of entrepreneurship, and the geography of entrepreneurship literature, focusing on the causes of the spatial heterogeneity of entrepreneurship. In the next two sections we summarize the insights from these two literatures.

2.1 Entrepreneurship and economic growth

The role of entrepreneurship in economic development has been studied for a long time, going back to Schumpeter (Schumpeter, 1934), Leibenstein (1968) and Baumol (1990). The entrepreneurship growth literature is mainly concerned with the question how and to what extent entrepreneurship affects economic growth. Even though the literature does not provide full consensus on the positive effects of entrepreneurship, there seems to be more evidence in favour of than against positive (causal) effects of entrepreneurship on economic growth (Audretsch et al., 2006; Bosma et al., 2018; Carree and Thurik, 2010; Fritsch, 2013). Key causal mechanisms are the creation and diffusion of innovations, and the competition created by entrepreneurs (Bosma et al., 2018). The direction and strength of the effect of entrepreneurship on economic growth depends on the type of context and type of entrepreneurship. Ambitious, opportunity and growth oriented types of entrepreneurship are more likely to lead to economic growth than self-employed, necessity based entrepreneurship (Bosma et al., 2018, 2011; Fritsch, 2013; Stam et al., 2011; Stam and Van Stel, 2011). In addition, entrepreneurship is most productive in conditions of inclusive and growth enhancing institutions (Bosma et al., 2018; Sobel, 2008). Entrepreneurship does not occur in a vacuum, but is very much a local event (Feldman, 2001). There is also substantial regional variation in the prevalence of entrepreneurship, with underlying causes being very much spatially bound (Alvedalen and Boschma, 2017; Guzman and Stern, 2015).

2.2 The geography of entrepreneurship

The geography of entrepreneurship literature has provided numerous insights into the role of different factors enhancing the prevalence of entrepreneurship in regions (Bosma et al., 2011; Stam, 2010; Stam and Spigel, 2018; Sternberg, 2009). We summarize the empirical geography of entrepreneurship literature with ten elements affecting the prevalence of entrepreneurship (cf. Stam, 2015; Stam and Van de Ven, 2019). The first element, formal institutions, provides the fundamental preconditions for economic action (Granovetter, 1992) and for resources to be used productively (Acemoglu et al., 2005). Formal institutions are not only a precondition for economic action to take place, they also affect the way entrepreneurship is pursued and the welfare consequences of entrepreneurship (Baumol, 1990). Informal institutions in particular the entrepreneurship culture, which reflects on the degree to which entrepreneurship is valued in society, also have strong effects on the prevalence of entrepreneurship, (Fritsch and Wyrwich, 2014). Networks of entrepreneurs provide an information flow, enabling an effective distribution of knowledge, labour and capital (Malecki, 1997). A highly developed physical infrastructure (including both traditional transportation infrastructure and digital infrastructure) is a key element of the context to enable economic interaction and entrepreneurship in particular (Audretsch et al., 2015). Access to finance—preferably provided by investors with entrepreneurial knowledge—is crucial for investments in uncertain entrepreneurial projects with a long-term horizon (see e.g. Kerr and Nanda, 2009). Leadership provides direction for the entrepreneurial ecosystem. This leadership is critical in building and maintaining a healthy ecosystem (Feldman, 2014) and involves a set of 'visible' entrepreneurial leaders who are committed to the region (Feldman and Zoller, 2012). The high levels of commitment and public spirit of regional leaders might be a reflection of underlying norms dominant in a region (Olberding, 2002). Perhaps the most important condition for entrepreneurship is the presence of a diverse and skilled group of workers ('talent': see e.g. Acs and Armington, 2004; Glaeser et al., 2010; Lee et al., 2004; Qian et al., 2013). An important source of opportunities for entrepreneurship can be found in knowledge, from both public and private organizations (see e.g. Audretsch and Lehmann, 2005). In addition, the presence of financial means in the population to purchase goods and services—preferably locally, but possibly also on a further distance—is essential for entrepreneurship to occur at all. The presence of demand thus is an important element of the entrepreneurial ecosystem. Income and purchasing power in a region is both a cause and an effect of entrepreneurship in a region (Berkowitz and DeJong, 2005), hinting at the role of feedback effects in the evolution of entrepreneurial ecosystems. Finally, the supply of support services by a variety of intermediaries can substantially lower entry barriers for new entrepreneurial projects, and reduce the time to market of innovations (see e.g. Clayton et al., 2018; Howells, 2006; Zhang and Li, 2010).

2.3 An entrepreneurial ecosystem framework

To understand the long-term development of (regional) economies and the role of entrepreneurship, the approaches of economic growth and geography of entrepreneurship need to be combined. Entrepreneurship plays a double role: it is the output variable in the geography of entrepreneurship approach, and it is the input variable in the economic growth approach. To complicate matters even more, entrepreneurship and economic growth also affect the inputs of the geography of entrepreneurship approach, for example with serial entrepreneurs becoming venture capitalists and creating networks; and with economic growth leading to growth in demand, investments in knowledge, and congestion effects in the physical environment. One solution to these conceptual complications is to build on complex systems approaches (Arthur, 2013; Hidalgo and Hausmann, 2009; Ostrom, 2010; Simon, 1962) to develop and use a complex systems perspective on the evolution of entrepreneurial economies (Feld and Hathaway, 2020; Roundy et al., 2018; Stam and Van de Ven, 2019). A complex systems perspective is able to integrate the geography of entrepreneurship and the entrepreneurship and economic growth literature. We build on the integrative model of entrepreneurial ecosystems by Stam and Van de Ven (2019), which includes institutional arrangements and resource endowment elements (see Fig. 1). The model includes three key mechanisms: interdependence and coevolution of elements, upward causation of the ecosystem on entrepreneurship, and downward causation of entrepreneurial outputs on the quality of the ecosystem (Stam and Van de Ven, 2019).

The empirical literatures on the geography of entrepreneurship and economic growth reveal several factors to be of relevance in explaining the spatial heterogeneity in entrepreneurship. This suggests that there is a limited set of factors that affects the prevalence of entrepreneurship in a region. The insights from the empirical literature on the geography of entrepreneurship and economic growth can be integrated into one figure (see Fig. 1), reflecting an entrepreneurial ecosystem framework with ten elements (cf. Stam, 2015; Stam and Spigel, 2018; Stam and Van de Ven, 2019). This framework with ten elements provides a compromise between other frameworks with five (Vedula and Kim, 2019), six (Isenberg and Onyemah, 2016), seven (Radosevic and Yoruk, 2013) and 14 elements (Ács et al., 2014). We build on these frameworks and develop them further by separating inputs and outputs of the system, providing an academically grounded set of elements, and using empirical indicators more closely reflecting productive entrepreneurship (Baumol, 1990; Schumpeter, 1934).

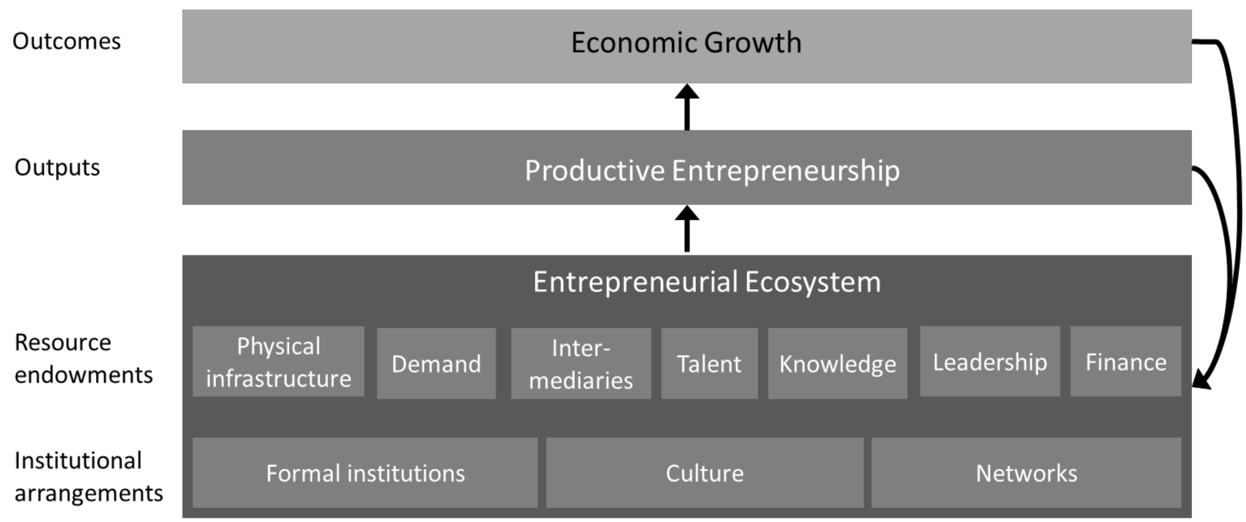


Fig. 1. Elements and outputs of the entrepreneurial ecosystem (adapted from Stam, 2015; Stam and Van de Ven, 2019).

3. Measuring entrepreneurial ecosystems

The ecosystem framework discussed above identifies ten key elements of an entrepreneurial ecosystem. While we do not claim to be exhaustive, ten ecosystem elements should be able to capture the most essential conditions for entrepreneurship to flourish. In this section, we discuss how we source data from a large variety of datasets to compose credible, accurate and especially comparable metrics of entrepreneurial ecosystems. Since there is no perfect dataset available for measuring entrepreneurial ecosystems, we have to compose one, with imperfections that we will discuss. This is also an invitation for follow-up research to improve our metrics when new data becomes available.

There are several existing metrics studies on the regional level that focus on themes closely related to entrepreneurship, especially in the European Union. For example the regional competitiveness index (RCI) (Annoni and Dijkstra, 2019), which measures the general competitiveness of a region including factors such as human capital and infrastructure. While the RCI and other studies such as the Regional Innovation Scoreboard (RIS) include several key indicators related to entrepreneurship, none of these explicitly focus on entrepreneurship. This is why a study starting from a clearly defined framework and explicitly focusing on productive entrepreneurship provides a novel and valuable contribution to the understanding of entrepreneurial conditions in a region. We thus set out to operationalize the entrepreneurial ecosystem elements into measurable variables at the appropriate geographical level. First, we discuss the boundaries of an ecosystem to determine the relevant level of analysis. Then we shortly illustrate the main data sources and describe the operational measures of each ecosystem element (for an overview see Table 1).

3.1 Level of analysis

The outputs and outcomes of entrepreneurial ecosystems are the result of a complex set of actors and factors that occur in a temporal and varying regional setting. As Feldman and Lowe (2015, p. 1785) rightly state there is often a disconnect "between the theoretical definition of a region as integrated contiguous space and the political and census geography for which data are readily available". In addition, since ecosystems are continuously evolving and are not limited to a specific sector, it is hard to precisely determine their boundaries (Stam and Van de Ven, 2019). The primary demarcation criterium should be the spatial reach of the causal mechanisms involved. This does not lead to one straightforward unit or spatial level of analysis. First, given the multiplicity of causal mechanisms involved in nurturing entrepreneurship, there will be different spatial reaches: for talent it may be the daily urban system (within a 50 mile radius), while for credit it may be the local bank, and for venture capital a two hour drive radius (which may overlap with the regional level in large countries, but may be beyond the national level for small countries). Second, there is a spatial nestedness of contexts: formal institutions at the municipal, regional, national and supranational level may be important context conditions. These first two considerations make it difficult to delineate the spatial boundary of entrepreneurial ecosystems from a causal mechanism point of view.

From a practitioners' point of view, the stakeholders of entrepreneurial ecosystems, the relevant boundaries will again be different depending on their role in the ecosystem. For civil servants it will be a particular jurisdiction, while for entrepreneurs it may be a multiplicity of layered (regional, national) or connected ecosystems (different city-regions). To determine the spatial level of analysis (although almost always imperfect) we therefore search for a common spatial denominator in combination with data availability (to allow for comparisons). It should be kept in mind that even though we choose a spatial unit to represent the entrepreneurial ecosystem, entrepreneurial ecosystems are not closed containers, but open systems.

In the European context, the most relevant spatial level of analysis is between the municipal and national level, since the spatial reaches of the different elements are most likely to overlap with regional boundaries (e.g. the 50 mile radius for talent). The regional level in Europe is best defined through the NUTS 2 classification, which identifies 281 geographical regions[1] over the 27 member states and the United Kingdom. The boundaries of NUTS 2 regions are based on existing administrative boundaries and population thresholds. The population of a NUTS 2 unit is roughly between 800,000 and 3 million people (European Commission, 2018).

While for some countries and/or indicators data is available on the more fine-grained NUTS 3 level, this was not the case for most countries or indicators we are interested in. We therefore decided to keep the unit of analysis at NUTS 2 as this would enable us to cover a larger set of regions all over Europe. Including a large set of regions is important because it enables comparison, one of the main goals of this paper. This is a first step and future studies could dive deeper into certain topics or countries and use more detailed data to do so. By defining entrepreneurial ecosystems at the NUTS 2 level we use the same region size as the recent study by Stam and Van de Ven (2019) but instead of one country we include all countries in the European Union and the United Kingdom.

A disadvantage of looking at regions is that data on a regional level is, for most countries, scarcer than national data. However, the European Union performs several large data collection exercises on regional level to inform regional policy, which results in the availability of a fairly large amount of regional data. Furthermore, we use web scraping to create new metrics at the NUTS 2 level. Finally, we use several national measures to account for the aforementioned spatial nestedness of for example institutions. This combination of data on different geographical levels is discussed in detail for each element below and summarized in Table A1 in the appendix.

[1] We remove seven French and Spanish regions that are located in either Africa or South America as there is limited data available for these regions and we perceive them as significantly different from the European regions.

3.2 Data sources and element construction

To measure the entrepreneurial ecosystem elements we combine data from various sources and complement this with data obtained by web scraping. For most elements we use very specific datasets, e.g. for finance we use the regional venture capital data of Invest Europe and for formal institutions the Quality of Government Survey. While for other elements we use specific indicators from existing datasets on related topics, e.g. the accessibility of a region from the Regional Competitiveness Index (RCI) for physical infrastructure or the percentage of innovative SME's that collaborate from the Regional Innovation Scoreboard (RIS) for networks. The data sources used for each element are described in detail below and in Table A1 in the appendix.

When operationalizing the ecosystem elements, our aim is to get the most robust measure possible with the lowest number of indicators. In doing so we consider and combine the accuracy – do they accurately capture what we aim to measure? – the credibility – can the sources be confidently relied on? – and the comparability of data sources – is comparable data available for all regions? For accuracy reasons we choose to measure some elements with multiple indicators, but for credibility and comparability reasons we sometimes have to resort to one indicator per element. In the discussion we will elaborate on how the operationalization of the elements can be improved in the future.

We choose to measure some elements with multiple indicators for two reasons. First, some elements such as institutions are multi-faceted and hard to capture in one variable. In particular, there is a certain spatial nestedness when studying regional ecosystems. A similar argument applies to some elements which can be measured on a more general level and in a more specific manner for entrepreneurs, such as the education level of the workforce and specific entrepreneurial skills. We thus combine variables to capture these various dimensions of one element.

Seven of the ten elements are constructed by combining multiple indicators. For those elements we calculate the element score by first standardizing the individual measures (mean as 0 and standard deviation of 1). This ensures that the different measures each have a proportionate influence on the composite indicator. We then take the average of the standardized measures.

To measure four of our variables, high-growth firms, unicorns, leadership, and the number of incubators, we use the location of individual organizations to calculate a regional aggregate measure. The methodology of geocoding and region allocation for these measures is as follows. First, we use the nominatim package in R to geocode the given locations using OpenStreetMap (OpenStreetMap, 2019; Rudis, 2019). This is an online map which allows users to pass a list of locations into the software and obtain their coordinates. For the few regions without a match in this procedure we manually search and add its coordinates. Subsequently, we used Eurostat shapefiles to determine in which NUTS 2 region these coordinates are located. These shapefiles contain an exact overview of the NUTS 2 boundaries (Eurostat, 2019). We then use the rgdal package in R to assign the coordinates to the corresponding NUTS 2 region (Bivand et al., 2019; Eurostat, 2019). With this procedure we are able to assign all except for about 0.1% of the organizations to a region. We manually searched the remaining organizations and located the remaining geocodes through the browser tool of OpenStreetMap. After this we were able to assign all organizations for all four variables to a region. For each of the four variables we then count the number of organizations/firms in each NUTS 2 region and divide this by the population of the region to obtain our final measure.

For a few indicators, in some countries, data is only available at the NUTS 1 level. In those cases we follow the approach of previous measurement studies and impute the NUTS 1 values for the NUTS 2 regions (Annoni and Dijkstra, 2019; Hollanders et al., 2019; Léon et al., 2016). Table 1 provides an overview of the empirical indicators and data source for each element while Table A1 in the appendix provides a more detailed description for each measure.

Table 1.

Operationalisation of the indicators of entrepreneurial ecosystem elements and output.

Elements	**Description**	**Empirical indicators**	**Data source**
Formal institutions	The rules of the game in society	Two composite indicators measuring the overall quality of government (consisting of scores for corruption, accountability, and impartiality) and the ease of doing business	Quality of Government Survey (QOG) and the World

			Bank Doing Business Report
Entrepreneurship culture	The degree to which entrepreneurship is valued in a region	A composite measure capturing the regional entrepreneurial culture, consisting of entrepreneurial motivation, cultural and social norms, importance to be innovative and trust in others	Global Entrepreneurship Monitor (GEM) and European Social Survey (ESS)
Networks	The connectedness of businesses for new value creation	Percentage of SMEs that engage in innovative collaborations as a percentage of all SMEs in the business population	Regional Innovation Scoreboard (RIS)
Physical Infrastructure	Transportation infrastructure and digital infrastructure	Four components in which the transportation infrastructure is measured as the accessibility by road, accessibility by railway and number of passenger flights and digital infrastructure is measured by the percentage of households with access to internet	Regional Competitiveness Index (RCI)
Finance	The availability of venture capital and access to finance	Two components: The average amount of venture capital per capita and the percentage of SMEs that is credit constrained	Invest Europe and European Investment Bank (EIB)
Leadership	The presence of actors taking a leadership role in the ecosystem	The number of coordinators on H2020 innovation projects per capita	CORDIS (Community Research and Development Information Service)
Talent	The prevalence of individuals with high levels of	Four components: The percentage of the population with tertiary education, the percentage of the working population	Eurostat and the Global

	human capital, both in terms of formal education and skills	engaged in lifelong learning, the percentage of the population with an entrepreneurship education, the percentage of the population with e-skills	Entrepreneurship Monitor (GEM)
New Knowledge	Investments in new knowledge	Intramural R&D expenditure as percentage of Gross Regional Product	Eurostat
Demand	Potential market demand	Three components: disposable income per capita, potential market size expressed in GRP, potential market size in population. All relative to EU average.	Regional Competitiveness Index (RCI)
Intermediate services	The supply and accessibility of intermediate business services	Two components: the percentage of employment in knowledge-intensive market services and the number of incubators/accelerators per capita	Eurostat and Crunchbase
Output	Entrepreneurial output	The number of Crunchbase firms founded in the past 5 years per capita	Crunchbase
	Unicorn output	The absolute number of unicorns in the region founded in the last ten years	CB Insights and Dealroom

3.4 Formal institutions

Well-functioning institutions are essential for entrepreneurship (Granovetter, 1992). Even when fundamental conditions of the institutional framework, e.g. property rights, are in place, the quality of these institutions affect entrepreneurship (Baumol, 1990; Boudreaux and Nikolaev, 2019; Webb et al., 2019). To operationalize this element, we use a generic and an entrepreneurship specific indicator. These indicators cover two different aspects of the institutional environment, namely the overall quality of government and the regulatory framework for businesses.

To operationalize the quality of government we use the Quality of Government study (QOG), which is the largest sub national governance study that has been performed (Charron et al., 2019). The Quality of Governance study has been used in numerous other studies and is a reliable measure of institutional quality (Charron et al., 2015). The quality of government indicator consists of three components: corruption, accountability and impartiality. These are each measured by a large, regional, citizen survey and complemented by the World Governance Indicators on a national level. The survey questions measure both experiences and perceptions of citizens with institutions in the particular region of the respondent (Charron et al., 2019). This measure thus accounts for the nestedness of the regional variation in quality of governance within national institutions.

To measure the entrepreneurship specific regulatory framework we use a composite indicator: the Ease of doing business index from the World Bank, which incorporates seven elements concerning business regulations at the national level (World Bank, 2014). These elements are highly linked to national regulations and as such a national measure is sufficient for this indicator. By combining this entrepreneurship specific national measure with the regional measure for the quality of governance we arrive at a measure capturing a combination of general and entrepreneurship specific institutions.

3.5 Entrepreneurship culture

The next element, culture, represents an informal institution. Entrepreneurship culture can be described as how much entrepreneurship is valued and stimulated in a society (Fritsch and Wyrwich, 2014). The cultural context can have a substantial effect on entrepreneurship by influencing the aspirations of entrepreneurs and whether people are likely to become an entrepreneur at all (Wyrwich et al., 2016).

To measure entrepreneurship culture we use four indicators: entrepreneurial motivation and cultural and social norms encouraging new business activity from the Global Entrepreneurship Monitor (GEM) measured at the country level (Bosma and Kelley, 2019), and the perceived importance of being innovative and creative, and trust in others from the European Social Survey[2] measured at the NUTS 2 level (Norwegian Center for Research Data, 2014)[3]. Again, we combine

[2] Data on these variables is missing for six regions, for these regions we calculated the culture score based on the two indicators for which data was available. We performed robustness checks in which we set the value for these indicators to the European average and in which we removed these regions. Both did not significantly affect our results, proving the robustness of this choice.

[3] Stam and Van de Ven (2019) use the number of new firms per 1,000 inhabitants as an alternative measure of culture. We initially aimed to combine our current indicator with this data. However, there is (not yet) a harmonized dataset on this variable for all European NUTS 2 regions and we thus had to use a combination of OECD, Eurostat, and national statistics offices to construct this variable (see Table A1). These data sources were not consistent in their

entrepreneurship specific measures with a more general measure of the regional culture (trust). This general indicator is important because in societies where people trust others it is for example easier to have economic interaction and invest in the first place (Zak and Knack, 2001).

3.6 Networks

When actors in a region are well connected in networks this allows information, labour and knowledge to flow to firms which can use it most effectively (Malecki, 1997). Networks are essential for entrants as it helps new firms to build social capital, which firms can leverage to get access to resources, information and knowledge (Eveleens et al., 2017; van Rijnsoever, 2020). The connections between firms can be measured through their cooperation projects. Our focus on entrepreneurship entails that we specifically want to measure cooperation on innovative projects. Therefore, we measure networks as the number of Small and Medium Enterprises (SMEs) that collaborate on innovation projects as percentage of all SMEs in a specific region. These SMEs will not all necessarily be entrepreneurial firms, but the focus on innovation projects means this measure captures the kind of productive collaboration that is likely to contribute to entrepreneurial output. We therefore believe that this is the best data currently available. In addition, the size of SMEs (enterprises with between 10 and 250 employees) matches with our focus on entrepreneurial growth since it does not include micro firms (less than 10 employees) or large firms, both of which are less relevant for our research goal. We use the data from the RIS, complemented with the European Innovation Scoreboard (EIS) for countries with only one NUTS 2 region. The RIS and EIS base their data on the Community Innovation Survey, a large survey on innovation activity including thousands of enterprises in every country in the European Union (Arundel and Smith, 2013).

3.7 Physical infrastructure

Physical infrastructure is essential for economic interaction between actors and thus essential for entrepreneurship as well (Audretsch et al., 2015). In this highly digital world not only physical infrastructure enables this interaction but also digital infrastructure. Digital infrastructure provides

definitions and data demarcations. Hence, we deemed the validity of this alternative measure to be questionable and we excluded this measure from our analyses. We did perform a robustness test in which we combined the birth rate of new firms with our current culture measure. The results of our analyses remained largely identical.

the opportunity to meet other actors, even if they are not in close physical proximity. Therefore, it is important to include this when creating an empirical measure of infrastructure. For our indicator we follow the approach of the RCI which uses the accessibility by road, accessibility by railway and number of passenger flights to measure the physical (transportation) infrastructure of a region (for details see Table A1). To this we add a measure for the digital infrastructure of a region, which is the percentage of households with access to internet and also available from the RCI (Annoni and Dijkstra, 2019).

3.8 Finance

An important condition for starting a new firm and growing an existing firm is access to capital (see e.g. Kerr and Nanda, 2009; Samila and Sorenson, 2010). We measure the availability of capital with two indicators: the amount of venture capital and the percentage of SMEs that is finance constrained. This is again a combination of an entrepreneurship specific and a general measure. It is valuable to add a measure of finance constrained firms because this is not limited to one specific form of finance and thus takes into account that firms may use different financial resources in different countries (Criscuolo and Menon, 2015).

Venture capital is measured as the average amount of venture capital in the last five years per capita. The data for this variable is from Invest Europe, an association of private capital providers which conducts research on private equity activity in Europe (Invest Europe, 2020). The percentage of finance constrained SMEs is taken from the investment survey by the European Investment Bank (Alanya et al., 2019). SMEs are enterprises with less than 250 employees. They are considered finance constrained when they either were rejected for loans or received less than applied for, or were discouraged to apply because it was too expensive or they expected to be turned down. The use of data on SMEs does, similarly to the measure for networks, not fully overlap with our focus on productive entrepreneurship but is again the best data available.

3.9 Leadership

Leadership in an entrepreneurial ecosystem is necessary to provide the actors in the ecosystem a certain direction or vision to work towards and to make the ecosystem function more effectively (Normann, 2013). Leadership can be provided by individual leaders but also by collaborative efforts that try to guide the system in a certain direction. Since leadership is an intangible concept it is quite hard to measure and remains understudied (Sotarauta et al., 2017). In our study we operationalize leadership as the number of project coordinators of Horizon2020 innovation projects in a region.[4] We thus follow the approach of Stam and Van de Ven (2019) who use the number of innovation project leaders as their operationalization for leadership. Although this measure is not limited to entrepreneurial leaders, it does capture whether there are organizations in a region that are willing to initiate new and innovative projects. These organizations, either public or private, are likely to create collective action in entrepreneurial ecosystems. To construct this variable we use the CORDIS database which contains data on 23,693 innovation projects that are subsidized as part of the Horizon 2020 program of the European Union (CORDIS, 2019; European Commission, 2019). We then use the geocoding approach outlined in section 3.3 to create our leadership indicator, the number of innovation leaders per capita.

3.10 Talent

Human capital (or talent) encompasses the skills, knowledge and experience possessed by individuals (Stam and Van de Ven, 2019). Human capital is a critical input for entrepreneurship and has been shown to be linked to new firm formation (see e.g. Acs and Armington, 2004; Glaeser et al., 2010). It is clearly a broad concept which asks for several empirical measures to properly cover its different facets. We break human capital down into two different components, general human capital and entrepreneurship-specific human capital (Becker, 1964; Rauch and Rijsdijk, 2013). We use two measures for the general human capital component, both from Eurostat (Eurostat, 2020). The first measure is the percentage of population having completed tertiary education and the second measure is the percentage of population aged 25-64 that participates in education or training (lifelong learning).

Entrepreneurship specific human capital is directly related to start-up activities (Brüderl et al., 1992; Rauch & Rijsdijk, 2013). We include two measures, the quality of entrepreneurship and business education from the GEM (Bosma and Kelley, 2019), and the percentage of population

[4] Horizon 2020 is the research and innovation program funded by the European Commission. It encompasses private-public partnerships working on innovation projects with the aim to stimulate economic growth in the European Union (European Commission, 2019).

with high level e-skills from Eurostat (Eurostat, 2020). The inclusion of digital skills is important because digital literacy is essential for working in any type of enterprise in the current digital society. In addition, a lot of productive entrepreneurship nowadays involves some digital aspect.

3.11 Knowledge

The creation of new knowledge by either private or public organizations provides new business opportunities (Kim et al., 2012; Qian et al., 2013). It is therefore an important source of entrepreneurship. We measure this element as the intra-mural R&D expenditure as a share of the total Gross Regional Product (GRP). This measure includes R&D spending in both public and private sectors. The higher the investment in R&D the more new knowledge is likely to be produced which can then be translated into business opportunities. The data for this variable is available in both the Regional Competitiveness Index (Annoni and Dijkstra, 2019) and Regional Innovation Scoreboard (Hollanders et al., 2019). We choose to use the data from the RCI as this is available at the NUTS 2 level for a larger number of regions.

3.12 Demand

The purchasing power and potential demand for goods and services is important for entrepreneurs, since it will only be interesting to market new products if the population has the financial means to buy them. Several studies have shown that market growth increases firm entry (Eckhardt and Shane, 2003; Sato et al., 2012). Even though most firms nowadays serve larger markets than just those in their own region, it is important for start-ups to have a potential regional market which they can easily access (Cortright, 2002; Reynolds et al., 1994; Schutjens and Stam, 2003). We measure the demand using data from the RCI which combines three measures (Annoni and Dijkstra, 2019). The measures are disposable income per capita, potential market size expressed in GRP and potential market size expressed in population. This measure captures both consumer demand and demand from existing businesses in the region.

3.13 Intermediate services

Intermediate services or producer services can help producers to start a new enterprise and market an innovation. This support can substantially lower entry barriers for new entrepreneurial projects and speed up the introduction of innovations (Howells, 2006; Zhang and Li, 2010). For this element we again combine a general and an entrepreneurship specific measure. We operationalize the general measure as employment in knowledge intensive market services, which represents the general availability of intermediate services, such as legal, marketing, accountancy and consultancy services. The required data is available in Eurostat (Eurostat, 2020).

For the specific measure we look at incubators and accelerators as intermediate service providers. These organizations specifically aim to help people with innovative ideas to start their own companies. Incubators and accelerators normally provide various services such as access to networks of entrepreneurs and training in business skills (Cohen et al., 2019; Eveleens et al., 2017; van Weele et al., 2017). Several studies have shown that incubators and accelerators can significantly contribute to the success of start-ups (see for recent reviews Ayatse et al. (2017) and Eveleens et al. (2017)). Since these organizations are put in place to support entrepreneurs and can improve the performance of new firms, it is important to include them in the analysis. For this variable we scraped a total of 950 incubators and accelerators from the Crunchbase website (Crunchbase, 2019). We then use the geocoding approach outlined in section 3.3 to determine the number of incubators per capita. Note that we measure the prevalence of intermediate services in general, and incubators and accelerators in particular, but not the quality of these services per se.

3.14 Entrepreneurial Ecosystem Index

To determine the quality of entrepreneurial ecosystems we explore the option of combining the measures of the ten elements of the entrepreneurial ecosystem to calculate an index. The calculation is done using the same method as applied in Stam and Van de Ven (2019). This approach relies on the crucial assumption that all ten elements are of equal importance in the ecosystem as we standardize the value for the different elements. This is clearly a very agnostic approach as one could think of reasons why certain elements should be given more weight than others. Some studies have investigated this and found that certain factors matter more than others (see e.g. Corrente et al. (2019)). However, these studies used other elements and data and it is therefore not possible to directly transfer these weights to our data. We are aware that the index we create in this manner will not be a final solution. Instead, we really present it here as a first step to determine the quality of entrepreneurial ecosystems using the metrics we have developed in the previous sections. We also perform a principal components analysis in the next section, which does not rely on the assumption that all components are equally important, as alternative method of combining the elements. Subsequently, we also perform a series of robustness checks on the index. Finally, we present a future research agenda on ways to further improve the measurement of the quality of entrepreneurial ecosystems that includes giving weights to elements.

To calculate the index we first standardize the composite indicators which we have created for each element. This ensures that all elements get similar weights in the creation of the index. Subsequently, to enable normalizing the standardized values we take the inverse natural log of the standardized values. This is necessary because normalizing requires division by the mean, which is 0 after standardization. We then normalize the element values by setting the European average of each element to 1 and by letting all other regional values deviate from this. If an element in a region performs less than average this results in a value between 0 and 1, above average performing regions have a value above 1. This allows us to compute an index value based on the ten elements and compare the quality of different entrepreneurial ecosystems. We calculate the Entrepreneurial Ecosystem Index (EEI) in three ways. First, in an additive way (E1 + E2 +…En) where regions with an average value on each element will thus score an index value of 10. Second, to better account for the systemic nature of the entrepreneurial ecosystem, we also calculate the index in a multiplicative manner (E1*E2*…En). The disadvantage of the normalization around 1 in both these indices is that values above 1 have a stronger effect on the index than below average values which are between 0 and 1. We therefore take the natural logarithm to let the values oscillate symmetrically around 0: this logarithmic way (log(E1) + log(E2) +….log(En)) is our third index value.

3.15 Output

The output of the entrepreneurial ecosystem is productive entrepreneurship (see Fig. 1). This kind of entrepreneurship contributes to the output of the economy and consequently leads to aggregate value creation, which is the outcome of the system (Baumol, 1990). Previous research has shown that proxies of productive entrepreneurship have strong positive effects on economic growth and job creation (Criscuolo et al., 2014; Haltiwanger et al., 2013; Stam et al., 2011; Wong et al., 2005). Productive entrepreneurship is a subset of total entrepreneurship and thus requires another measure than, for example, the total number of new firms.

In this study we take the number of new firms (i.e. founded less than 5 years ago) that are registered in Crunchbase as our measure for entrepreneurial output (Crunchbase, 2019; Dalle et al., 2017). Crunchbase predominantly captures venture capital oriented innovative entrepreneurial firms and largely ignores companies without a growth ambition and is thus a good source for data on productive entrepreneurship (Dalle et al., 2017). We choose the five year timeframe to ensure that we select firms who experience their growth phase during the same time period (2015-2019) as most of our indicators are measured (see Table A1). This time period also helps to limit our sample towards innovative new firms as Crunchbase also includes incumbent, long established innovative firms. The data on Crunchbase mostly comes from two channels, a community of contributors and a large investor network. This data is then validated with other data sources using AI and machine-learning algorithms.

A limitation of the Crunchbase dataset is that it is uncertain if the coverage of start-ups is equal among the different countries. Overall, we find that around 0.2% of all new European firms are registered in Crunchbase.[5] This varies between 0.003% and 1.5% and follows a (zero-inflated) normal distribution.[6] We further acknowledge that not all start-ups are innovative (cf. Autio et al., 2014), and are also aware that our measure of entrepreneurial output does not capture all innovative activity in the economy. Nevertheless, Crunchbase is currently the most comprehensive dataset available to measure innovative new firms as entrepreneurial output (Dalle et al., 2017). Crunchbase is increasingly used for academic research (Dalle et al., 2017; Nylund and Cohen, 2017). We also explored using the ORBIS data of Bureau Van Dijk as an alternative (Bureau van Dijk, 2020; Dalle et al., 2017). However, we perceived this data to be inadequate for our purposes. First, the serial correlation between the different years in the database was very low. Second, the data also contained disproportionally large differences between countries which were hard to render and would thus impede cross country regional comparisons.

[5] The data sources for the number of new firms in each country is outlined in table A1.

[6] However, one specific region (UKI3 – Inner London West) has an extreme value of 11,3%. This extreme value is also reflected in our Crunchbase output measure. Further research showed that this was partly the result of all central London based start-ups being assigned to UKI3 instead of to both UKI3 and UKI4 (UKI4 – Inner London East) due to these regions having the same name in Crunchbase. We therefore decided to combine these regions to form one Inner London region. Nevertheless, this region remained an extreme value and to achieve a normal distribution for the regression analyses we performed a Tukey transformation ($\lambda = 0.2$) on this variable. In the next section we discuss the remaining transformations in our data preparations.

In addition to the Crunchbase output measure, we use a measure for extreme entrepreneurial output in the form of unicorns, which are young private firms valued above $1 billion. Data was collected from CB Insights which keeps a list of current unicorn companies all over the world (CB Insights, 2020). As these are so rare, all firms founded in the last ten years that acquired unicorn status were included. This was done by scraping data from historical web pages of the internet archive and cross-checking this with Dealroom data (Dealroom, 2020).[7] We then used the geocoding procedure to allocate these unicorns to a total of 20 NUTS 2 regions. As such, unicorns are a very rare and selective form of productive entrepreneurship that is only present in a small number of regions. Besides unicorns being a very rare type of organization, the value of unicorns as a measure of productive entrepreneurship has also been a topic of discussion (see for example Aldrich and Ruef, 2018; Economist, 2019), which is why we only use this as an additional output measure.

3.16 Extreme values

Since the European Union covers a large and diverse set of regions, the data show a lot of variety. In particular, for the measures of knowledge, intermediate services, leadership and entrepreneurial output there are a few regions that have very high values (up to 14 times the standard deviation). Even though this variation is plausible, these outliers do disproportionally influence the correlation results and regression results. Most importantly, for the regions that score extremely high on one particular indicator, the index for the quality of the entrepreneurial ecosystem is disproportionally influenced by that indicator. This does not reflect the systemic nature of entrepreneurial ecosystems as argued in the existing academic literature (Spigel, 2017; Stam, 2015). Therefore, we performed two transformations on the data to provide better interpretable results. First, before the standardization of the composite indicators we cap the maximum value at four standard deviations of the mean (for more information on the standardization procedure see section 3.14 on index calculation).[8] In practice this means that we change the values for UKI3&4 (Inner London) of the Crunchbase output, leadership, and intermediate services measures, for DE91 (Braunschweig) of knowledge (as a result of the high R&D intensity), and for DK01 (Hovedstaden)

[7] The data from Dealroom is similar but less extensive than the Crunchbase data. We used it for the unicorn variable because Dealroom keeps a list of all European unicorns.
[8] We performed a robustness test in which we implemented a cap at three standard deviations, this required capping a total of twelve regional values but did not significantly change our findings.

of leadership. Without these transformations the high deviations of these values skew the outcomes of the normalization process in such a way that only a few regions achieve above average scores. Second, we set the maximum score for any single element to five in order to prevent a disproportionate influence of strong performing ecosystem elements on the overall index. We perform a number of robustness checks on the construction of our index which we discuss in appendix C.

4. Quantifying and qualifying entrepreneurial ecosystems in Europe

4.1 Descriptive statistics

The descriptive statistics of the empirical measures for the ten ecosystem elements, entrepreneurial outputs, and the index scores are shown in Table 2. In total our data covers 273 NUTS 2 regions divided over the 27 EU member states and the United Kingdom.

Table 2

Descriptive statistics

	N	Mean	Standard Deviation	Minimum	Maximum
Crunchbase output	273	0.852	1.018	0.014	5.000 (31.958)
Unicorn output	273	0.179	1.051	0.000	15.000
Formal institutions	273	1.000	0.812	0.098	3.497
Culture	273	0.990	1.072	0.026	5.000 (6.219)
Networks	272	0.984	1.147	0.117	5.000 (6.110)
Physical Infrastructure	272	0.907	1.060	0.058	5.000 (8.916)
Finance	273	0.993	0.823	0.053	5.000 (6.907)
Leadership	273	0.703	1.111	0.181	5.000 (25.751)
Talent	273	0.968	0.964	0.072	5.000 (11.913)
Knowledge	273	0.722	1.031	0.109	5.000 (33.503)
Demand	273	1.000	0.932	0.032	4.761
Intermediate services	273	0.697	1.014	0.082	5.000 (56.011)
EE index additive	272	8.934	6.462	1.262	35.081
EE index multiplicative	272	323.444	2778.293	0.000	39364.109
EE index logarithmic	272	-6.061	7.157	-21.962	10.581

Notes: The uncorrected maximum value of each element is presented between brackets. We do not have data for all elements for Aland, a small island region of Finland, so the total number of regions for which we calculate the index is 272.

We see a large variation for several variables, from regions with less than 2 percent of the EU average to regions who have over 56 times the average value. These findings are nevertheless in line with our expectations since we study regions across different countries and levels of development. Looking at the three index values that we calculated using the methods of Stam and Van de Ven (2019), we find that the difference between the smallest and largest value for the multiplicate index is a factor 10^{15}. This difference is disproportionately large in comparison with the actual variation in the data as a result of the multiplicative way of calculating the index. Hence, we deem the external validity of the multiplicative index to be insufficient and instead use the additive and the logarithmic indices in our further analyses. Throughout the remainder of this study we primarily focus on the additive index due to the intuitiveness of its interpretation.

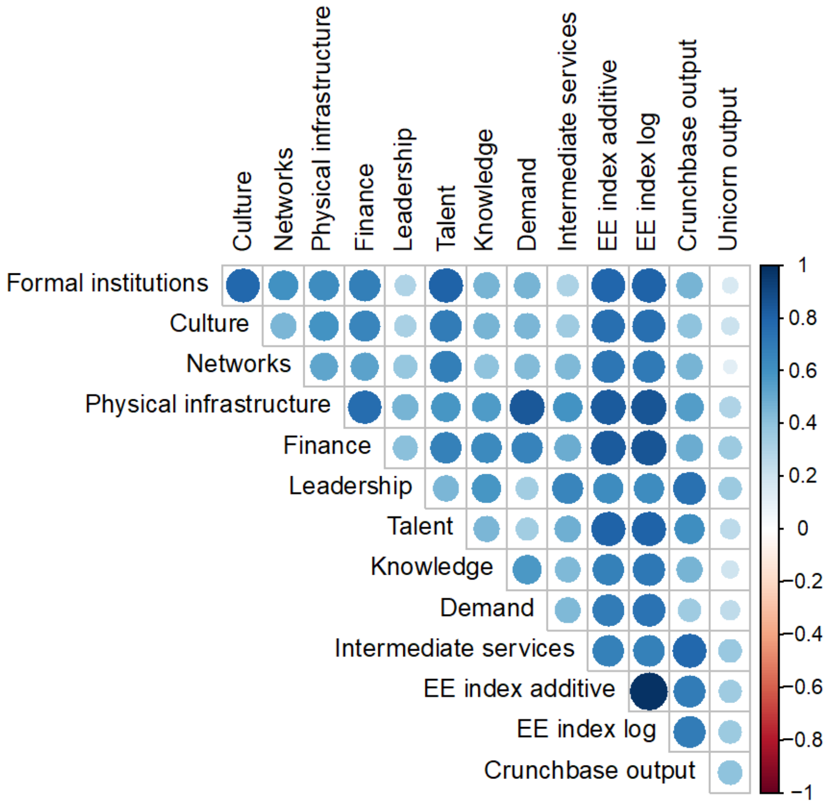
4.2. Interdependence between entrepreneurial ecosystem elements

Table 3 shows the correlations between the different elements of the entrepreneurial ecosystem, the index and the outputs. We see high, positive and significant correlations between all of the elements of the ecosystem.[9] The strong positive correlations illustrate the interdependencies in the entrepreneurial ecosystem. This corresponds to the results shown in Stam and Van de Ven (2019) and confirms the systemic nature of entrepreneurial ecosystems. Considering the entrepreneurial output measures, we see positive and significant correlations with all elements, and with the entrepreneurial ecosystem indices we constructed. These correlations provide some support for the proposition regarding upwards causation, stating that the ecosystem elements influence the occurrence of productive entrepreneurship.

[9] For an overview of the numeric correlation coefficients with p-values see Table A2.

Table 3.

Correlation matrix (correlation coefficient is indicated by colour and the significance level by size, only correlations that are significant at 5% level are shown)



We use a network methodology to show the interdependencies between the ten elements in Fig. 5. Physical infrastructure and finance take the most central position in the interdependence web. This central role is supported by the finding that physical infrastructure and finance have respectively eight and six interdependencies with a correlation above 0.5 (Fig. 6a), followed by formal institutions and talent which each have five. When looking at the interdependencies with correlations above 0.6, formal institutions and finance are the most central in the interdependence web with each five correlations above 0.6 (Fig. 6b). Physical infrastructure, culture, and talent also have central positions with four correlations above 0.6. Finally, formal institutions and physical infrastructure each have two interdependencies with correlations above 0.7 (see table A2). This provides an indication for a potential role of these elements as fundamental conditions of the entrepreneurial ecosystem.

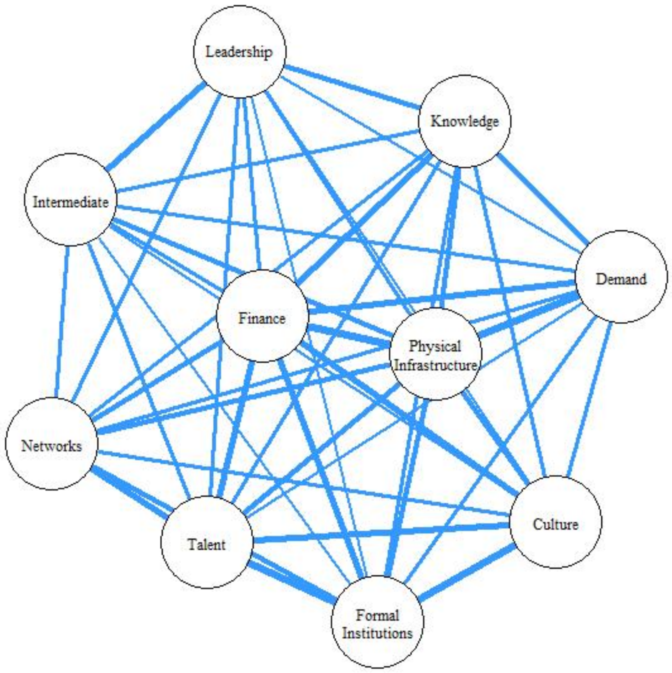


Fig. 5.

Interdependence web of entrepreneurial ecosystem elements with the blue lines indicating positive correlations. The edge weight is defined based on the correlation strength.

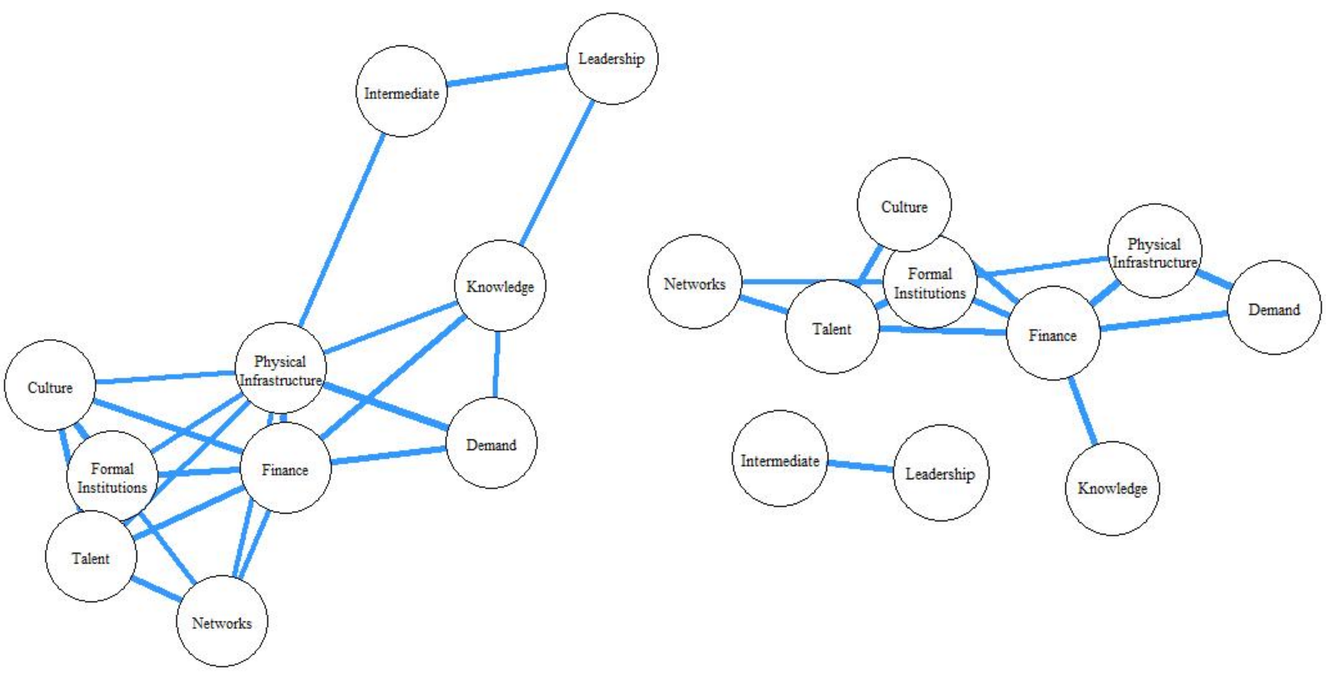


Fig. 6a. and 6b.

Interdependence webs of entrepreneurial ecosystem elements with correlations above 0.5 (left) and 0.6 (right)

To further explore the interdependencies we performed principal component analysis (PCA) on the 10 individual elements. This method does not assume that all elements are equally important as the elements are assigned different loadings. The results are presented in Table 4, the first component explains 44.9% of the variance and has loadings of 0.21 or higher for all components. The three elements with the highest loadings are finance (0.40), physical infrastructure (0.38), talent (0.36), and formal institutions (0.35). This result confirms our findings from the interdependence graphs which show a strongly connected set of elements with a central role for these elements. The second component, which explains an additional 12.8% of the variation, has loadings of 0.21 or higher for six components. Similarly, the third component explains 12.4% of the variation and here six elements have loadings above 0.24. The results of the PCA thus confirm the strong interdependencies between the entrepreneurial ecosystem elements. The high loadings of all elements also show that all elements are related to the underlying dimensions of the data and are thus likely to be relevant to the entrepreneurial ecosystem.

Table 4.

Principal components analysis

	PC1	**PC2**	**PC3**
Proportion of Variance	0.449	0.128	0.124
Standard Deviation	2.119	1.132	1.113
Cumulative Variance	0.449	0.577	0.701
Formal institutions	0.348	-0.476	0.161
Culture	0.308	-0.164	0.437
Networks	0.212	-0.393	-0.367
Physical infrastructure	0.379	0.041	-0.381
Finance	0.397	0.133	-0.041
Leadership	0.249	0.478	0.154
Talent	0.356	-0.256	0.357
Knowledge	0.222	0.207	0.240
Demand	0.334	0.039	-0.541
Intermediate	0.297	0.484	0.032

4.3. Entrepreneurial Ecosystem Index

We now use the Entrepreneurial Ecosystem Index (EEI) to provide insight in the strongest and weakest entrepreneurial ecosystems in Europe. The scores for the ten highest (Fig. 2) and lowest ranking (Fig. 3) regions are shown in the bar graphs below. The highest scoring regions are, as expected, mainly Western European and densely populated, while the lowest scoring regions are mainly Bulgarian and Greek rural regions. To look at the different Entrepreneurial Ecosystems in more detail, Fig. 4 shows the map of Europe with all NUTS 2 regions coloured based on the value of the EEI. The highest index values can be found in European capital regions, such as London, Helsinki, and Stockholm. Many regions in Eastern Europe show very low index values as do some of the more rural areas in Spain. The map supports the claim that there is a substantial difference between urban and rural areas. Most of the high-scoring regions include large cities. In section 4.6 we will compare our index to existing variables and rankings (such as GDP and the RCI) to discuss the added value of the EEI.

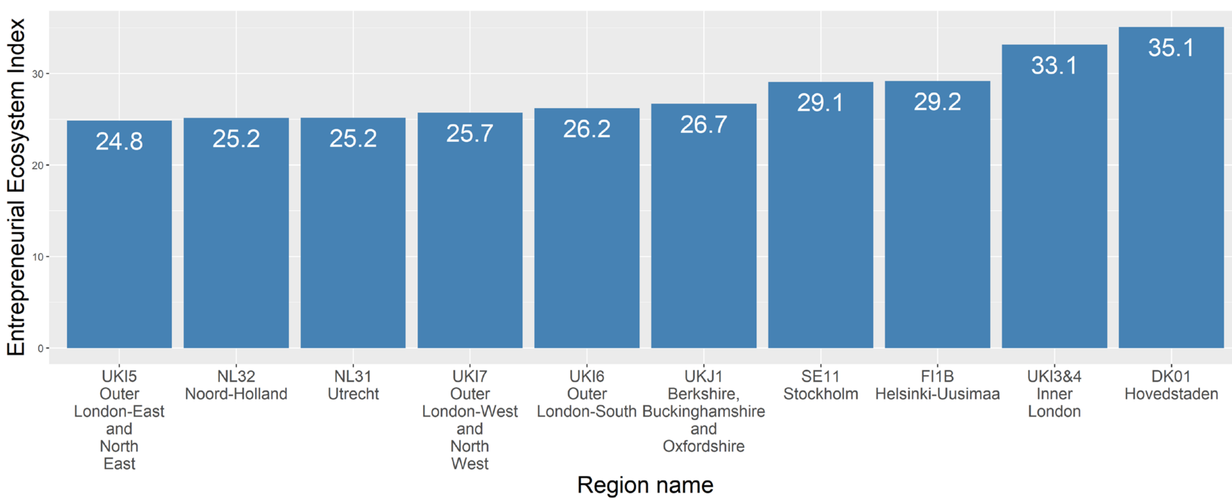


Fig. 2

NUTS 2 regions with the highest Entrepreneurial Ecosystem Index scores.

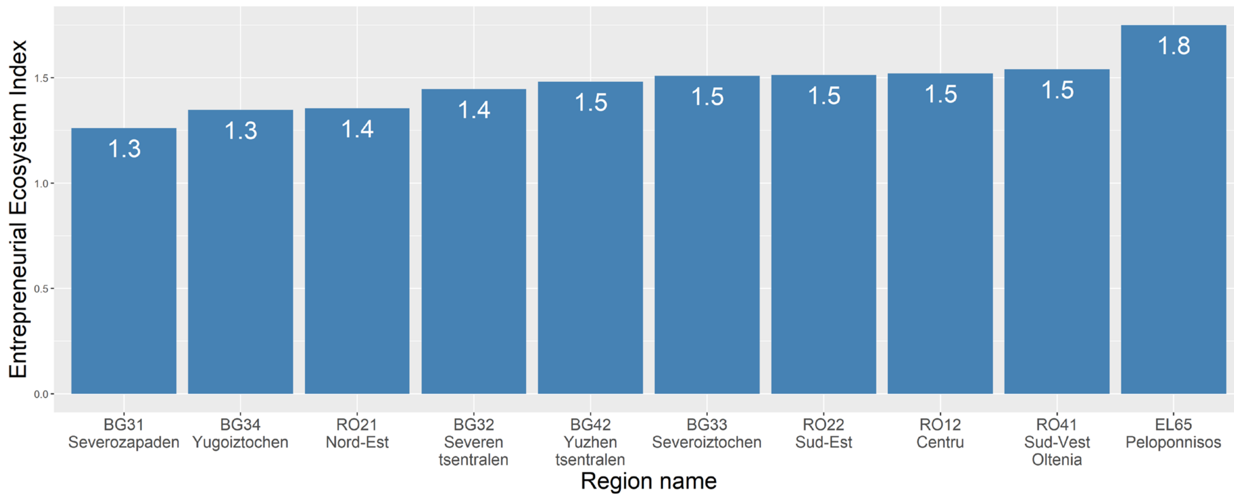


Fig. 3

NUTS 2 regions with the lowest Entrepreneurial Ecosystem Index scores.

The EEI simply adds the different elements and subsequently creates a ranking based on the total value of the ten elements. A different approach to classify regions is to use a cluster analysis on the ten ecosystem elements, which creates groups of regions which are closest to each other on the scores for each element. Particularly, we use k-means clustering which minimizes the total intra-cluster variation (sum of squared errors) using Euclidean distance measures for an a priori fixed number of clusters (Tan et al., 2018). K-means clustering is the most popular clustering technique and was originally proposed by MacQueen (1967). The number of clusters is a parameter that has to be set by the user. After considering the total intra-cluster variation, the average silhouette of clusters, the gap statistic, and the interpretability of the outcomes we selected the approach with three clusters. The results (Table 5) show a large first cluster which includes low-performing regions, including for example Athens, Budapest and Sicily. The second cluster forms a middle group and includes Manchester, Cologne and Luxembourg. Finally, the third cluster is the smallest group with high performing regions including Berlin, London, and Brussels. Table 5 shows a clear pattern in the average index values of the regions across the clusters. This is further confirmed through the visual representation of the clusters which shows that the cluster distribution closely aligns with the scores of the EEI (figure B1 in the appendix). Using clustering as an alternative method to classify regions we thus find highly similar results to the index.

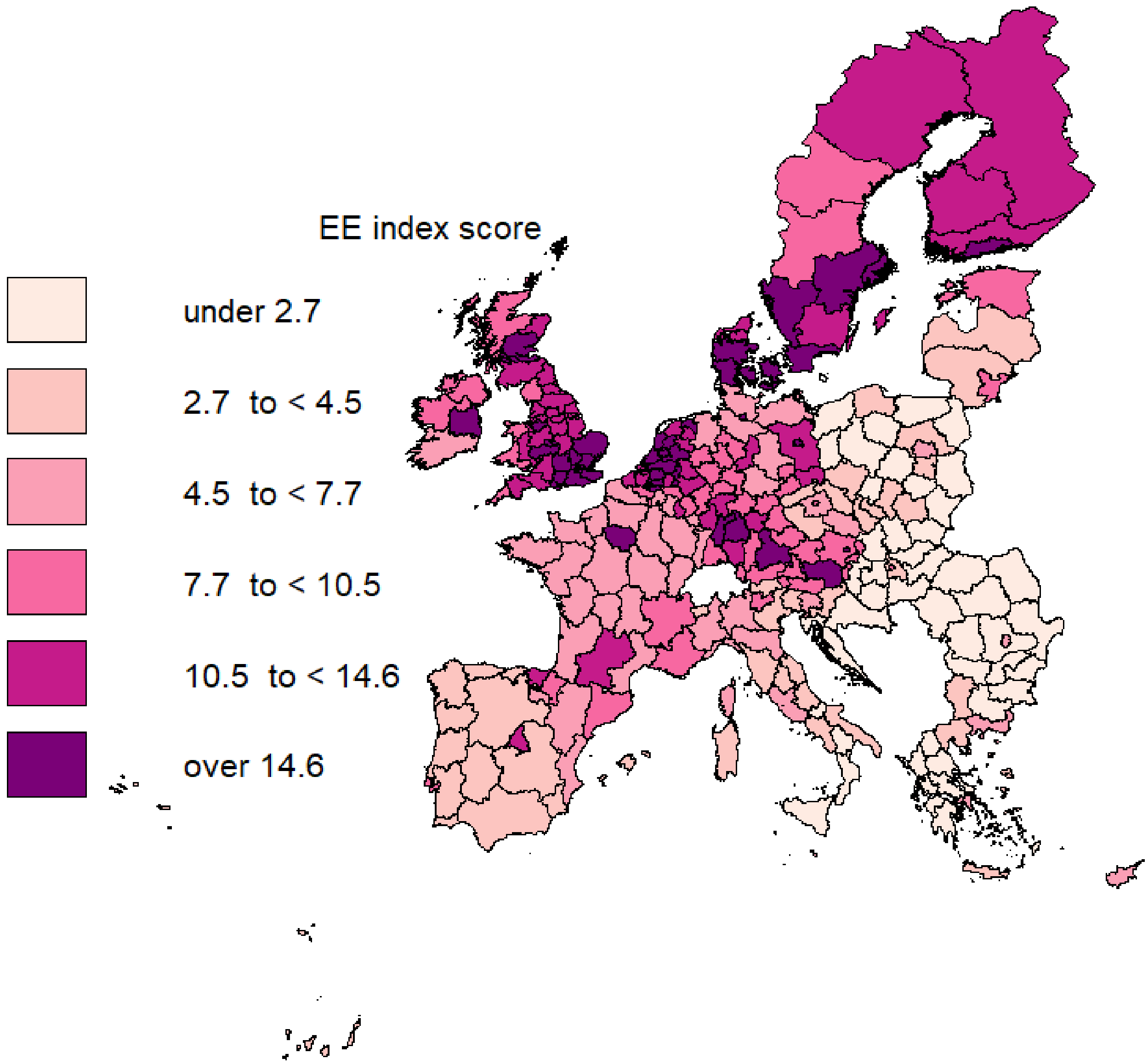


Fig 4.

Map of NUTS 2 regions showing Entrepreneurial Ecosystem Index (273 regions are divided among groups of equal size).

Table 5.

Summary statistics of index and output by cluster

	Cluster 1 (N=148)	Cluster 2 (N=95)	Cluster 3 (N=29)	Overall (N=272)
Number of Crunchbase enterprises				
Mean (SD)	0.575 (0.767)	0.777 (0.554)	2.51 (1.64)	0.852 (1.02)
Median [Min, Max]	0.337 [0.0143, 5.00]	0.685 [0.178, 4.47]	2.18 [0.288, 5.00]	0.466 [0.0143, 5.00]
EE index additive				
Mean (SD)	4.34 (2.25)	12.0 (2.62)	22.3 (5.13)	8.93 (6.46)
Median [Min, Max]	3.58 [1.26, 11.4]	11.8 [7.58, 19.1]	21.4 [14.4, 35.1]	7.66 [1.26, 35.1]
EE index log				
Mean (SD)	-11.3 (4.75)	-1.39 (2.34)	5.32 (2.52)	-6.06 (7.16)
Median [Min, Max]	-11.5 [-22.0, -1.56]	-1.52 [-6.34, 3.51]	5.09 [0.970, 10.6]	-5.29 [-22.0, 10.6]
Unicorn output				
Mean (SD)	0.0203 (0.183)	0.0316 (0.176)	1.48 (2.91)	0.180 (1.05)
Median [Min, Max]	0 [0, 2.00]	0 [0, 1.00]	0 [0, 15.0]	0 [0, 15.0]

4.4. Entrepreneurial Ecosystem Index and entrepreneurial output

After discussing the creation and reliability of the EEI we now use regression analysis to study if regions with better ecosystems indeed have higher entrepreneurial outputs. Table 5 showed that the regions in the third cluster with a high EEI score have significantly higher outputs than the middle and laggard clusters. This provides an indication that the relation between the index and entrepreneurial output is not linear. This indication is confirmed through a scatterplot (Fig. 7).

An increase in performance on the index thus goes together with a disproportionately large increase in the number of start-ups. To capture this nonlinearity in the relation between the quality of an entrepreneurial ecosystem and its entrepreneurial outputs, we performed a regression with quadratic effects, for the results see table B2 in the appendix. The quadratic effects are significant ($p<0.001$) and show that the relation between the index and the entrepreneurial output is indeed nonlinear. However, the convex relation between the index and output means that adding quadratic effects forces a quadratic curve on the observations that looks like a U-shape. This is an unintended side effect of using quadratic effects in a linear regression.[10]

[10] We use the two lines test of Simonsohn (2018) to confirm that there is indeed no U shape relation between the index and output.

Therefore, to better capture the nonlinear relationship between the index and output we instead perform a piecewise linear regression. This allows breakpoints in the regression line that is fitted to the data. The results are presented in Figure 7 and Table 7. The breakpoint that optimizes model fit for the additive index is located at an index score of 19.[11] At this point the slope quite sharply increases from 0.08 to 0.39. For both the first and the second line we find a positive and significant relation between the index and entrepreneurial output ($p<0.01$). The large increase in the slope of the regression line further shows that at the high end of the index there is a small group of regions with very high performance regarding entrepreneurial output. This corresponds with our findings in the cluster analysis presented above.[12] The results of the regression analyses with the unicorn output as dependent variable can be found in Table B3 in the appendix[13] and are consistent with the findings reported in Table 7.

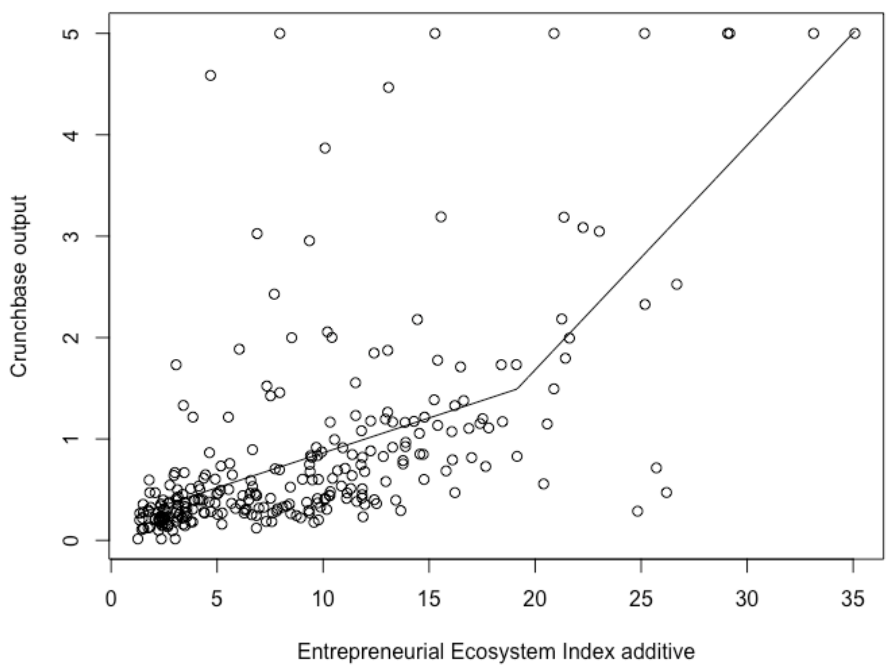


Fig. 7 Scatter plot with line showing the fitted values of the piecewise linear regression

[11] We get a very similar result when we allow for a structural break in the line. The main method shown assumes a continuous relation and uses the R package *'segmented'* (Muggeo, 2008).
[12] As an additional robustness test, we also performed the regression analyses using the principal components (see appendix C). The results of these regressions showed nearly identical results, serving as evidence for the robustness of our results.
[13] We only report these findings in the appendix because of the limited number of regions with unicorn observations (20 out of 272).

Table 7.
Piecewise linear regression

	Crunchbase output	
	(1)	(2)
EE index additive	0.081***	
	(0.014)	
Difference slope EE index additive	0.315**	
	(0.146)	
EE index logarithmic		0.047***
		(0.009)
Difference slope EE index logarithmic		0.475***
		(0.088)
Constant	0.103	1.034***
	(0.120)	(0.129)
Observations	272	272
R^2	0.422	0.431
Adjusted R^2	0.415	0.425
F Statistic	65.213***(df=3;268)	67.697***(df=3;268)

*Notes: Clustered standard errors at country level in parentheses. * p<0.05 ** p<0.01 *** p<0.001*

The scatter plot (Fig. 7) shows that even with the piecewise linear regression there are several regions that do not seem to fit the plotted line. Particularly, we see some regions with very high entrepreneurial output and low index values. The regions in the upper left corner of the plot are for example Malta and Luxembourg which are known for very favourable tax regulations, which in previous studies have been shown to increase the amount of high growth entrepreneurship (Guzman and Stern, 2015). On the other hand, regions with high index values but relatively low entrepreneurial output are for example several outer London regions.[14] These are all regions with good conditions for entrepreneurship but located very close to even more 'vibrant' entrepreneurial areas which attract a disproportionate share of innovative new firms (e.g. Inner London).

Since we compare regions in different countries, it is important to check whether the index does not just capture between country differences but also has explanatory power within countries. We

[14] For some regions this also has to do with the fact that the data for some indicators is measured at the NUTS 1 level, as is described in table A1.

therefore run a multilevel analysis with country-specific intercepts and our EEI. The results of the multilevel analysis are presented in Table 8. The index variables still show a significant and positive relation with the entrepreneurial output ($p<0.001$). Adding country specific intercepts improves the model as evidenced by an increased R^2 as well as the likelihood ratio tests. The random effects in the bottom of the table show the regional variation (σ^2) and the variation between countries (τ_{00}). The strong coefficient and significance of our index when we compare regions within countries shows the robustness of the index. In addition, the high regional variation supports our choice to focus on the regional level when studying entrepreneurial ecosystems.

Finally, to test the robustness of our index we perform seven robustness checks to study its sensitivity to different calculation methods and extreme values. These robustness test include the use of the principal components instead of the index as independent variable as well as different ways of calculating the index. A description of the robustness checks and their results are presented in appendix C. The findings prove that our index is robust.

Table 8.

Multilevel analysis

	Crunchbase output	
	(1)	(2)
EE index additive	0.149 ***	
	(0.008)	
EE index logarithmic		0.168 ***
		(0.010)
Constant	-0.285 *	2.202 ***
	(0.144)	(0.203)
Random Effects		
σ^2	0.32	0.34
τ_{00}	0.32 country	0.76 country
ICC	0.50	0.69
N	23 country	23 country
Observations	267	267
Marginal R^2	0.594	0.570
Conditional R^2	0.798	0.868

*Notes: This regression excludes countries that exist of only a single NUTS 2 region, which are Luxembourg, Malta, Estonia, Cyprus and Latvia. Standard errors in parentheses. * p<0.05; ** p<0.01; *** p<0.001*

4.6 Comparison with existing indices

In the previous sections we showed that the EEI proved to be a good predictor of productive entrepreneurship. However, the question remains whether the EEI also outperforms existing rankings on similar topics. Therefore, we compare the EEI with two existing indices, first the RCI which measures the competitiveness of a region and second the RIS which measures the innovative ability in the region. Furthermore, we also include the GRP per capita as an alternative measure. The results (Table 9) show that, as expected, there are strong correlations between our index and the RCI (0.92), the RIS (0.90) and GDP (0.77). However, our index clearly has a higher correlation with both entrepreneurial output measures than any of the alternatives. This shows that there is clearly added value in developing theory-based metrics to measure the quality of regional entrepreneurial ecosystems and that our measure captures dimensions of the ecosystem which go beyond the level of economic development of a region.

Table 9.

Correlation table indices and outcomes

	EE index add	EE index log	RCI 2019	RIS 2019	GRP per capita	Crunchbase output
EE index log	0.985****					
RCI 2019	0.920****	0.941****				
RIS 2019	0.900****	0.902****	0.885****			
GRP per capita	0.773****	0.782****	0.820****	0.724****		
Crunchbase output	0.696****	0.695****	0.573****	0.588****	0.585****	
Unicorn output	0.351****	0.362****	0.300****	0.286****	0.281****	0.400****

Note: *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

5. Discussion and conclusions

The objective of this paper was to quantify and qualify regional economies with an entrepreneurial ecosystem approach. Quantification involved measuring the ten key elements of entrepreneurial ecosystems with a wide range of data sources. Qualification involved applying a network methodology to provide insight in the interdependencies between the elements and the construction of an EEI to approximate the overall quality of entrepreneurial economies. Finally, we related the elements and the index to entrepreneurial outputs.

We answered three main research questions. First, how can we compose a harmonized data set to measure the quality of key elements of entrepreneurial economies? We built on prior entrepreneurial ecosystem research and composed a harmonized data set that measures each element of entrepreneurial ecosystems in the context of 273 regions in 28 European countries. To do so we sourced a wide variety of data from existing datasets and online databases. However, not all elements could be measured in a fully satisfactory way. Often, more adequate data is available, but not at the same regional level or for all regions. An example is the data we used for the finance element: we prefer to have a composite indicator that includes objective data on the supply of different types of entrepreneurial finance. However, this is currently only available for venture capital in European regions. This could be improved by also including bank loans and crowdfunding. Another example is the data we used for the networks element. Even though the data provided on the engagement of SMEs in innovative collaborations is very informative, additional network data on collaborative networks and influencer networks, for example based on Twitter or LinkedIn data, could enrich the diagnosis of entrepreneurial ecosystems (Eveleens, 2019). This kind of network data would also allow for more refined measures of network diversity, density and centrality. For other elements there is no straightforward data available and new variables had to be constructed. This was the case for leadership, for which others (Stam and Van de Ven, 2019) have constructed country specific indicators, and we have created a pan-European indicator. However, even though this indicator provides information on the prevalence of (public-private) leadership in the context of European projects, improvements can be made to measure leadership that is relevant for the quality of entrepreneurial economies, for example with the prevalence of public-private regional partnerships (see Olberding, 2002). Overall, there is a significant trade-off between getting richer context-specific data (often only available in a relatively small number of regions) and getting widely available, harmonized data, which enables comparisons between regions. We invite other researchers to take up the gauntlet and improve these metrics further by collecting new and richer data.

Second, to what extent and how are the elements of entrepreneurial economies interdependent? We performed correlation, principal component, cluster, and network analyses to visualize the interdependencies between elements. These analyses revealed that entrepreneurial economies are systems with highly interdependent elements. Our analyses showed that physical infrastructure, finance, formal institutions, and talent take a central position in the interdependence web, providing a first indication of these elements as fundamental conditions for entrepreneurial ecosystems.

Third, how can we determine the quality of entrepreneurial economies? We answered this question by composing our Entrepreneurial Ecosystem Index and analysing its relation to entrepreneurial outputs. We used multiple data sources and metrics, including web scraping and geocoding, to determine entrepreneurial outputs at the regional level. We have shown that it is possible to measure the quality of entrepreneurial economies in a way that has external validity: showing a ranking of European regions and range of variation that is credible. Our analyses reveal the wide-ranging quality of entrepreneurial ecosystems in Europe, showing a large group of substantially lagging regions and a smaller group of leading regions. We also tested the internal validity using the fact that high quality entrepreneurial ecosystems are more likely to produce emergent properties, which we measured with indicators of productive entrepreneurship. The prevalence of innovative new firms is strongly positive and statistically significantly related to the quality of entrepreneurial ecosystems, as captured with differently constructed entrepreneurial ecosystem indices. This upward causation confirms earlier findings of Stam and Van de Ven (2019) and Vedula and Kim (2019). The current index is formed under the assumption that each element is equally important for the quality of the ecosystem, and while we find highly similar results when we challenge this assumption by employing principal component analysis, there is still a clear opportunity to improve the index in the future. We invite further research to study the respective importance of the ten elements for the quality of the entrepreneurial ecosystem and believe that the metrics developed in this study provide them with the opportunity to do so. In particular, future research should address if there are combinations of elements that are either necessary or sufficient for high outputs of productive entrepreneurship. Methods such as latent cluster analysis or qualitative comparative analysis can play an important role in doing this and thus improve our understanding of the workings of entrepreneurial ecosystems.

There are several additional opportunities for improving these metrics that deserve substantial attention in follow-up research. First, the internal validity of the index should be tested more carefully, in particular with other (more direct) tests of causality, with longer time lags between changes in the quality of entrepreneurial ecosystems and the resulting entrepreneurial outputs, and with some quasi-natural experiments in which a set of similar regions is confronted with substantially different changes in one or a few elements. In sum, we need to move from a comparative static analysis to a dynamic analysis, and for this we need longitudinal datasets. This would make it possible to better trace processes within entrepreneurial ecosystems (Spigel and Harrison, 2018) and allow us to measure the distinct properties of complex systems that arise from interdependencies, such as nonlinearity, emergence, tipping-points, spontaneous order, adaptation, and feedback loops. Second, even though Europe provides a wide variety of regions to develop and test our entrepreneurial ecosystem metrics, these metrics need to be developed and tested in other contexts as well, in large sets of regions in the US, Asia, Africa, and Latin America. Finally, statistical regions are not always overlapping with either the relevant jurisdictions or the spatial reach of the causal mechanisms involved (for example as related to culture and the provision of finance). Developing tailor made spatial units and taking into account the nestedness of elements (cities, in regions, in countries) and neighbourhood effects is also a challenge for future research. With the help of spatial econometrics spill-over effects between regions could be analysed. Our empirical research implicitly assumed an equal weight of all regional units. Future research can improve upon this by taking into account the differential (population, economic) size of regions, which might lead to more adequate regression analyses.

6. Policy implications

In spite of the popularity of the entrepreneurial ecosystem approach in science and policy, there is a scarcity of credible, accurate and especially comparable metrics of entrepreneurial ecosystems. In this paper, we bridge this gap and measure the quality of entrepreneurial ecosystems by collecting and combining the relevant data in a comprehensive set of metrics. These metrics are essential for data-and-dialogue-driven policy.

First, these metrics are an essential input for ex-ante policy diagnosis: to discover the weaknesses and strengths of entrepreneurial ecosystems. These weakness and strengths are always relative to other relevant regions, the benchmark. This is why the construction of large scale datasets is a necessity for regional policy. Benchmarking the region could also trigger policy learning from regions that have comparable entrepreneurial ecosystems. Tackling the weakest elements of entrepreneurial ecosystems is likely to provide the most efficient and effective way of improving the overall quality of the entrepreneurial ecosystem and stimulating productive entrepreneurship (Ács et al., 2014). However, a limitation in the application of our metrics is that they provide insight in where to look for improvement, but not on how this improvement should be achieved.

It is thus important to combine these metrics with qualitative insights about particular entrepreneurial ecosystems.

The metrics are also an essential input for ex-post policy evaluation, as they enable monitoring whether and to what degree the envisioned improvements of particular entrepreneurial ecosystem elements has been achieved, and whether this has resulted in an increase in productive entrepreneurship and economic growth. For this monitoring, regular measurement of the quality of the entrepreneurial ecosystem elements is essential. For structural economic policy, annual data points would suffice, but in the context of rapidly evolving crises, including the COVID-19 crisis, more frequent monitoring with quarterly or even monthly data might be needed.

However, entrepreneurial ecosystem policy can never be fully data driven: comprehensive planning is computationally intractable (i.e., practically impossible) in large regional entrepreneurial ecosystems (cf. Bettencourt, 2014). Data on social phenomena are likely to remain insufficient, and interdependencies between elements and their emergent properties are unlikely to remain stable over time. Entrepreneurial ecosystem metrics facilitate a collective learning process to improve regional economies: this process is a combination of data and dialogue. The diagnosis based on the metrics should, ex-ante, be used to facilitate dialogue between stakeholders of the entrepreneurial ecosystem about policy interventions, and facilitate, ex-post, a dialogue about the effectiveness of these interventions. Entrepreneurial ecosystem metrics are thus essential for data-and-dialogue-driven policy.

In sum, the entrepreneurial ecosystem approach, including the metrics we propose, provide the means to improve each and every region in its own way. In particular, the approach and its metrics provide a lens for public policy to better diagnose, understand and improve entrepreneurial economies.

7. References

Acemoglu, D., Johnson, S., Robinson, J.A., 2005. Chapter 6 Institutions as a Fundamental Cause of Long-Run Growth. Handb. Econ. Growth. https://doi.org/10.1016/S1574-

0684(05)01006-3
Acs, Z.J., Armington, C., 2004. The impact of geographic differences in human capital on service firm formation rates. J. Urban Econ. 56, 244–278. https://doi.org/10.1016/j.jue.2004.03.008
Ács, Z.J., Autio, E., Szerb, L., 2014. National Systems of Entrepreneurship: Measurement issues and policy implications. Res. Policy 43, 476–494. https://doi.org/10.1016/j.respol.2013.08.016
Aghion, P., David, P.A., Foray, D., 2009. Science, technology and innovation for economic growth: Linking policy research and practice in "STIG Systems." Res. Policy 38, 681–693. https://doi.org/10.1016/j.respol.2009.01.016
Alanya, A., Simpson, A., McHugh, S., 2019. EIB Group Survey on Investment and Investment Finance.
Aldrich, H.E., Ruef, M., 2018. Unicorns, gazelles, and other distractions on the way to understanding real entrepreneurship in the United States. Acad. Manag. Perspect. 32, 458–472. https://doi.org/10.5465/amp.2017.0123
Alvedalen, J., Boschma, R., 2017. A critical review of entrepreneurial ecosystems research: towards a future research agenda. Eur. Plan. Stud. 25, 887–903. https://doi.org/10.1080/09654313.2017.1299694
Annoni, P., Dijkstra, L., 2019. The EU Regional Competitiveness Index.
Arthur, W.B., 2013. Complexity Economics. Oxford University Press, Oxford.
Arundel, A., Smith, K., 2013. History of the Community Innovation Survey, in: Gault, F. (Ed.), Handbook of Innovation Indicators and Measurement. Edward Elgar, Cheltenham, pp. 60–87.
Audretsch, D.B., Heger, D., Veith, T., 2015. Infrastructure and entrepreneurship. Small Bus. Econ. 44, 219–230. https://doi.org/10.1007/s11187-014-9600-6
Audretsch, D.B., Keilbach, M.C., Lehmann, E.E., 2006. Entrepreneurship and Economic Growth. Oxford University Press, Oxford.
Audretsch, D.B., Lehmann, E.E., 2005. Does the knowledge spillover theory of entrepreneurship hold for regions? Res. Policy 34, 1191–1202. https://doi.org/10.1016/j.respol.2005.03.012
Autio, E., Kenney, M., Mustar, P., Siegel, D., Wright, M., 2014. Entrepreneurial innovation: The importance of context. Res. Policy 43, 1097–1108.

https://doi.org/10.1016/j.respol.2014.01.015
Ayatse, F.A., Kwahar, N., Iyortsuun, A.S., 2017. Business incubation process and firm performance: an empirical review. J. Glob. Entrep. Res. 7, 2. https://doi.org/10.1186/s40497-016-0059-6
Baumol, W.J., 1990. Entrepreneurship: Productive, Unproductive, and Destructive. J. Polit. Econ. 98, 893–921. https://doi.org/10.1086/261712
Becker, G.S., 1964. Human capital. New York.
Berkowitz, D., DeJong, D.N., 2005. Entrepreneurship and Post-socialist Growth. Oxf. Bull. Econ. Stat. 67, 25–46. https://doi.org/10.1111/j.1468-0084.2005.00108.x
Bettencourt, L.M.A., 2014. The uses of big data in cities. Big Data. https://doi.org/10.1089/big.2013.0042
Bivand, R., Keitt, T., Rowlingson, B., 2019. rgdal: Bindings for the "Geospatial" Data Abstraction Library. R package version 1.4-7. Cran 0.
Bosma, N., Content, J., Sanders, M., Stam, E., 2018. Institutions, entrepreneurship, and economic growth in Europe. Small Bus. Econ. 51, 483–499. https://doi.org/10.1007/s11187-018-0012-x
Bosma, N., Kelley, D., 2019. Global Entrepreneurship Monitor.
Bosma, N., Stam, E., Schutjens, V., 2011. Creative destruction and regional productivity growth: Evidence from the Dutch manufacturing and services industries. Small Bus. Econ. 36, 401–418. https://doi.org/10.1007/s11187-009-9257-8
Boudreaux, C.J., Nikolaev, B., 2019. Capital is not enough: opportunity entrepreneurship and formal institutions. Small Bus. Econ. 53, 709–738. https://doi.org/10.1007/s11187-018-0068-7
Brown, R., Mason, C., 2014. Inside the high-tech black box: A critique of technology entrepreneurship policy. Technovation 34, 773–784. https://doi.org/10.1016/j.technovation.2014.07.013
Brüderl, J., Preisendörfer, P., Ziegler, R., 1992. Survival Chances of Newly Founded Business Organizations. Am. Sociol. Rev. 57, 227–242.
Bureau van Dijk, 2020. Bureau van Dijk | Private company information – Orbis [WWW Document]. URL https://www.bvdinfo.com/en-gb (accessed 1.10.20).
Carree, M.A., Thurik, A.R., 2010. The Impact of Entrepreneurship on Economic Growth, in:

Handbook of Entrepreneurship Research. Springer New York, pp. 557–594. https://doi.org/10.1007/978-1-4419-1191-9_20

CB Insights, 2020. The Global Unicorn Club [WWW Document]. URL https://www.cbinsights.com/research-unicorn-companies (accessed 6.4.20).

Charron, N., Lapuente, V., Rothstein, B., 2019. Measuring the quality of Government at the subnational level and comparing results with previous studies.

Clayton, P., Feldman, M., Lowe, N., 2018. Behind the scenes: Intermediary organizations that facilitate science commercialization through entrepreneurship, in: Academy of Management Perspectives. Academy of Management, pp. 104–124. https://doi.org/10.5465/amp.2016.0133

Cohen, S., Fehder, D.C., Hochberg, Y. V., Murray, F., 2019. The design of startup accelerators. Res. Policy 48, 1781–1797. https://doi.org/10.1016/j.respol.2019.04.003

Commission, E., 2018. Regulation (EC) No 1059/2003 of the European Parliament and of the Council of 26 May 2003 on the establishment of a common classification of territorial units for statistics (NUTS).

CORDIS, 2019. EU research projects under Horizon 2020 (2014-2020) - Datasets [WWW Document]. URL https://data.europa.eu/euodp/en/data/dataset/cordisH2020projects (accessed 12.19.19).

Corrente, S., Greco, S., Nicotra, M., Romano, M., Schillaci, C.E., 2019. Evaluating and comparing entrepreneurial ecosystems using SMAA and SMAA-S. J. Technol. Transf. https://doi.org/10.1007/s10961-018-9684-2

Cortright, J., 2002. The Economic Importance of Being Different: Regional Variations in Tastes, Increasing Returns, and the Dynamics of Development. Econ. Dev. Q. 16, 3–16. https://doi.org/10.1177/0891242402016001001

Credit, K., Mack, E.A., Mayer, H., 2018. State of the field: Data and metrics for geographic analyses of entrepreneurial ecosystems. Geogr. Compass. https://doi.org/10.1111/gec3.12380

Criscuolo, C., Gal, P.N., Menon, C., 2014. The Dynamics of Employment Growth. OECD Sci. Technol. Ind. Policy Pap. 96. https://doi.org/10.1787/5jz417hj6hg6-en

Criscuolo, C., Menon, C., 2015. Environmental policies and risk finance in the green sector: Cross-country evidence. Energy Policy 83, 38–56.

https://doi.org/10.1016/j.enpol.2015.03.023

Crunchbase, 2019. Crunchbase [WWW Document].

Dalle, J.-M., Den Besten, M., Menon, C., 2017. Using Crunchbase for economic and managerial research Using Crunchbase for Economic and Managerial Research Matthijs den Besten †. https://doi.org/10.1787/6c418d60-en

Dealroom, 2020. European unicorns [WWW Document]. URL https://app.dealroom.co/lists/15129

Eckhardt, J.T., Shane, S.A., 2003. Opportunities and Entrepreneurship. J. Manage. 29, 333–349. https://doi.org/10.1177/014920630302900304

Economist, 2019. The trouble with tech unicorns - Tech's new stars have it all—except a path to high profits [WWW Document].

European Commission, 2019. Horizon 2020 | The EU Framework Programme for Research and Innovation [WWW Document]. URL https://ec.europa.eu/programmes/horizon2020/en (accessed 12.19.19).

Eurostat, 2020. Regional statistics by NUTS classification [WWW Document].

Eurostat, 2019. Eurostat [WWW Document]. URL ttps://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts (accessed 11.26.19).

Eveleens, C., 2019. Interfering with innovative entrepreneurship: How business incubation measures the performance of start-ups. Utrecht University.

Eveleens, C.P., van Rijnsoever, F.J., Niesten, E.M.M.I., 2017. How network-based incubation helps start-up performance: a systematic review against the background of management theories. J. Technol. Transf. 42, 676–713. https://doi.org/10.1007/s10961-016-9510-7

Feld, B., 2012. Startup Communities: Building an entrepreneurial ecosystem in your city. John Wiley & Sons, Inc. https://doi.org/10.1016/j.ijhydene.2011.08.022

Feld, B., Hathaway, I., 2020. The Startup Community Way: Evolving an Entrepreneurial Ecosystem. Wiley, Hoboken, NJ.

Feldman, M., Lowe, N., 2015. Triangulating regional economies: Realizing the promise of digital data. Res. Policy 44, 1785–1793. https://doi.org/10.1016/j.respol.2015.01.015

Feldman, M., Zoller, T.D., 2012. Dealmakers in Place: Social Capital Connections in Regional Entrepreneurial Economies. Reg. Stud. 46, 23–37.

https://doi.org/10.1080/00343404.2011.607808

Feldman, M.P., 2014. The character of innovative places: Entrepreneurial strategy, economic development, and prosperity. Small Bus. Econ. 43, 9–20. https://doi.org/10.1007/s11187-014-9574-4

Feldman, M.P., 2001. The Entrepreneurial Event Revisited: Firm Formation in a Regional Context. Ind. Corp. Chang. 10, 861–891. https://doi.org/10.1093/icc/10.4.861

Fritsch, M., 2013. New business formation and regional development: A survey and assessment of the evidence. Found. Trends Entrep. https://doi.org/10.1561/0300000043

Fritsch, M., Wyrwich, M., 2014. The Long Persistence of Regional Levels of Entrepreneurship: Germany, 1925–2005. Reg. Stud. 48, 955–973. https://doi.org/10.1080/00343404.2013.816414

Glaeser, E.L., Kerr, W.R., Ponzetto, G.A.M., 2010. Clusters of entrepreneurship. J. Urban Econ. 67, 150–168. https://doi.org/10.1016/j.jue.2009.09.008

Granovetter, M., 1992. Economic Institutions as Social Constructions: A Framework for Analysis. Acta Sociol. 35, 3–11. https://doi.org/10.1177/000169939203500101

Guzman, J., Stern, S., 2015. Where is Silicon Valley? Science (80-.). 347, 606–609. https://doi.org/10.1126/science.aaa0201

Haltiwanger, J., Jarmin, R.S., Miranda, J., 2013. Who creates jobs? Small versus large versus young. Rev. Econ. Stat. https://doi.org/10.1162/REST_a_00288

Hidalgo, C.A., Hausmann, R., 2009. The building blocks of economic complexity. Proc. Natl. Acad. Sci. U. S. A. 106, 10570–10575. https://doi.org/10.1073/pnas.0900943106

Hollanders, H., Es-Sadki, N., Merkelbach, I., 2019. Regional Innovation Scoreboard 2019.

Howells, J., 2006. Intermediation and the role of intermediaries in innovation. Res. Policy 35, 715–728. https://doi.org/10.1016/j.respol.2006.03.005

Invest Europe, 2020. Activity report 2007-2019 European Private Equity.

Isenberg, D., Onyemah, V., 2016. Fostering scaleup ecosystems for regional economic growth (innovations case narrative: Manizales-Mas and Scale Up Milwaukee. Innov. Technol. Governance, Glob. 11, 60–79.

Isenberg, D.J., 2010. How to start an entrepreneurial revolution. Harv. Bus. Rev. 88, 41–50.

Katz, B., Bradly, J., 2013. The metropolitan revolution: How cities and metros are fixing our broken politics and fragile economy. Brookings Institution Press.

Kerr, W.R., Nanda, R., 2009. Democratizing entry: Banking deregulations, financing constraints, and entrepreneurship. J. financ. econ. 94, 124–149. https://doi.org/10.1016/j.jfineco.2008.12.003

Kim, Y., Kim, W., Yang, T., 2012. The effect of the triple helix system and habitat on regional entrepreneurship: Empirical evidence from the U.S. Res. Policy 41, 154–166. https://doi.org/10.1016/j.respol.2011.08.003

Lee, S.Y., Florida, R., Acs, Z.J., 2004. Creativity and entrepreneurship: A regional analysis of new firm formation. Reg. Stud. 38, 879–891. https://doi.org/10.1080/0034340042000280910

Leibenstein, H., 1968. Entrepreneurship and Development. Am. Econ. Rev. 58, 72–83.

Léon, L.R., Izsak, K., Bougas, K., Soto, V., 2016. Regional Ecosystem Scoreboard.

Mack, E., Mayer, H., 2016. The evolutionary dynamics of entrepreneurial ecosystems. Urban Stud. https://doi.org/10.1177/0042098015586547

MacQueen, J., 1967. Some methods for classification and analysis of multivariate observations. Proc. fifth Berkeley Symp. Math. Stat. Probab. 1, 281–297.

Malecki, E.J., 1997. Entrepreneurs, networks, and economic development: A review of recent research, in: Katz, J.A. (Ed.), Advances in Entrepreneurship, Firm Emergence and Growth. CT:JAI Press, Greenwich.

Muggeo, V.M.R., 2008. segmented: An R package to Fit Regression Models with Broken-Line Relationships. R News. https://doi.org/10.1159/000323281

Normann, R., 2013. Regional Leadership: A Systemic View. Syst. Pract. Action Res. 26, 23–38. https://doi.org/10.1007/s11213-012-9268-2

Norwegian Center for Research Data, 2014. ESS Round 7: European Social Survey Round 7 Data, Data file edition 2.2.

Olberding, J.C., 2002. Does Regionalism Beget Regionalism? The Relationship between Norms and Regional Partnerships for Economic Development. Public Adm. Rev. 62, 480–491. https://doi.org/10.1111/0033-3352.00201

OpenStreetMap, 2019. OpenStreetMap [WWW Document]. URL https://www.openstreetmap.org/ (accessed 11.22.19).

Ostrom, E., 2010. Beyond markets and states: Polycentric governance of complex economic systems. Am. Econ. Rev. 100, 641–672. https://doi.org/10.1257/aer.100.3.641

Qian, H., Acs, Z.J., Stough, R.R., 2013. Regional systems of entrepreneurship: The nexus of human capital, knowledge and new firm formation. J. Econ. Geogr. 13, 559–587. https://doi.org/10.1093/jeg/lbs009

Radosevic, S., Yoruk, E., 2013. Entrepreneurial propensity of innovation systems: Theory, methodology and evidence. Res. Policy 42, 1015–1038. https://doi.org/10.1016/j.respol.2013.01.011

Rauch, A., Rijsdijk, S.A., 2013. The Effects of General and Specific Human Capital on Long-Term Growth and Failure of Newly Founded Businesses. Entrep. Theory Pract. 37, 923–941. https://doi.org/10.1111/j.1540-6520.2011.00487.x

Reynolds, P., Storey, D.J., Westhead, P., 1994. Cross-national Comparisons of the Variation in New Firm Formation Rates. Reg. Stud. 28, 443–456. https://doi.org/10.1080/00343409412331348386

Roundy, P.T., Bradshaw, M., Brockman, B.K., 2018. The emergence of entrepreneurial ecosystems: A complex adaptive systems approach. J. Bus. Res. 86, 1–10. https://doi.org/10.1016/j.jbusres.2018.01.032

Rudis, B., 2019. nominatim: Tools for Working with the “Nominatim” API. R package version 0.2.2.9000.

Samila, S., Sorenson, O., 2010. Venture capital as a catalyst to commercialization. Res. Policy 39, 1348–1360. https://doi.org/10.1016/j.respol.2010.08.006

Sato, Y., Tabuchi, T., Yamamoto, K., 2012. Market size and entrepreneurship. J. Econ. Geogr. https://doi.org/10.1093/jeg/lbr035

Schumpeter, J.A., 1934. The theory of economic development. Univ. Press - Harvard.

Schutjens, V., Stam, E., 2003. The Evolution and Nature of Young Firm Networks: A Longitudinal Perspective, in: Small Business Economics. pp. 115–134. https://doi.org/10.1023/A:1025093611364

Simon, H.A., 1962. The Architecture of Complexity. Proc. Am. Philos. Soc. 106, 467–482.

Simonsohn, U., 2018. Two Lines: A Valid Alternative to the Invalid Testing of U-Shaped Relationships With Quadratic Regressions. Adv. Methods Pract. Psychol. Sci. https://doi.org/10.1177/2515245918805755

Sobel, R.S., 2008. Testing Baumol: Institutional quality and the productivity of entrepreneurship. J. Bus. Ventur. 23, 641–655. https://doi.org/10.1016/j.jbusvent.2008.01.004

Sotarauta, M., Beer, A., Gibney, J., 2017. Making sense of leadership in urban and regional development. Reg. Stud. https://doi.org/10.1080/00343404.2016.1267340

Spigel, B., 2020. Entrepreneurial ecosystems. Theory, practice and future. Edward Elgar.

Spigel, B., 2017. The Relational Organization of Entrepreneurial Ecosystems. Entrep. Theory Pract. 41, 49–72. https://doi.org/10.1111/etap.12167

Spigel, B., Harrison, R., 2018. Toward a process theory of entrepreneurial ecosystems. Strateg. Entrep. J. 12, 151–168.

Stam, E., 2015. Entrepreneurial Ecosystems and Regional Policy: A Sympathetic Critique. Eur. Plan. Stud. 23, 1759–1769. https://doi.org/10.1080/09654313.2015.1061484

Stam, E., 2010. Entrepreneurship, Evolution and Geography, in: Boschma, R., Martin, R.L. (Eds.), The Handbook of Evolutionary Economic Geography. Edward Elgar, Cheltenham, pp. 307–348.

Stam, E., Hartog, C., Van Stel, A., Thurik, R., 2011. Ambitious entrepreneurship and macro-economic growth, in: Minniti, M. (Ed.), The Dynamics of Entrepreneurship. Evidence from the Global Entrepreneurship Monitor Data. Oxford University Press, Oxford, pp. 231–249.

Stam, E., Spigel, B., 2018. Entrepreneurial ecosystems, in: Blackburn, R., De Clerq, C., Heinonen, J. (Eds.), The SAGE Handbook of Small Business and Entrepreneurship. SAGE, London, pp. 407–422.

Stam, E., Van de Ven, A., 2019. Entrepreneurial Ecosystem Elements. Small Bus. Econ. 1–24.

Stam, E., Van Stel, A., 2011. Types of Entrepreneurship and Economic Growth, in: Szirmai, A., Naudé, W., Goedhuys, M. (Eds.), Entrepreneurship, Innovation, and Economic Development. Oxford University Press, Oxford.

Sternberg, R., 2009. Regional dimensions of entrepreneurship. Found. Trends Entrep. 5, 211–340. https://doi.org/10.1561/0300000024

Tan, P., Steinbach, M., Kumar, V., Karpatne, A., 2018. Introduction to data mining, Second. ed. Pearson Education.

Thurik, A.R., Stam, E., Audretsch, D.B., 2013. The rise of the entrepreneurial economy and the future of dynamic capitalism. Technovation 33, 302–310. https://doi.org/10.1016/j.technovation.2013.07.003

Tukey, J.W., 1957. On the Comparative Anatomy of Transformations. Ann. Math. Stat. 28, 602–632. https://doi.org/10.1214/aoms/1177706875 van Rijnsoever, F.J., 2020. Meeting, mating, and intermediating: How incubators can overcome weak network problems in entrepreneurial ecosystems, in: Research Policy. Elsevier B.V. https://doi.org/10.1016/j.respol.2019.103884

van Weele, M., van Rijnsoever, F.J., Nauta, F., 2017. You can't always get what you want: How entrepreneur's perceived resource needs affect the incubator's assertiveness. Technovation 59, 18–33. https://doi.org/10.1016/j.technovation.2016.08.004

Vedula, S., Kim, P.H., 2019. Gimme shelter or fade away: The impact of regional entrepreneurial ecosystem quality on venture survival. Ind. Corp. Chang. 28, 827–854. https://doi.org/10.1093/icc/dtz032

Webb, J.W., Khoury, T.A., Hitt, M.A., 2019. The Influence of Formal and Informal Institutional Voids on Entrepreneurship. Entrep. Theory Pract. 104225871983031. https://doi.org/10.1177/1042258719830310

Wong, P.K., Ho, Y.P., Autio, E., 2005. Entrepreneurship, innovation and economic growth: Evidence from GEM data. Small Bus. Econ. 24, 335–350. https://doi.org/10.1007/s11187-005-2000-1

World Bank, 2014. Doing business 2015: Going beyond efficiency. Washington, DC.

Wyrwich, M., Stuetzer, M., Sternberg, R., 2016. Entrepreneurial role models, fear of failure, and institutional approval of entrepreneurship: a tale of two regions. Small Bus. Econ. https://doi.org/10.1007/s11187-015-9695-4

Zhang, Y., Li, H., 2010. Innovation search of new ventures in a technology cluster: the role of ties with service intermediaries. Strateg. Manag. J. 31, 88–109. https://doi.org/10.1002/smj.806

Appendix A

Description of data

Table A1.

Description of indicator data sources

Element	Indicators	Measurement and description	Source	Geographical level	Year
Formal institutions	Quality of Governance indicators for Corruption, Impartiality, and Quality and accountability	Average of z-score for the three indicators (Corruption, Impartiality, and Quality and accountability) based on survey answers	Quality of Government Index	NUTS 2 NUTS 1 for BE, DE, EL, SE, and UK Country for IE and LT	2017
Formal institutions	Ease of doing business index	Index based on several dimensions: starting a business, dealing with permits, registering property, credit access, protecting investors, taxes, trade, contract enforcement and closing a business	World Bank Doing Business Report	Country	2015
Entrepreneurship culture	Entrepreneurial motivation	Percentage of early stage entrepreneurs motivated by a desire to improve their income or a desire for independence	Global Entrepreneurship Monitor	Country	2014
Entrepreneurship culture	Cultural and social norms	The extent to which social and cultural norms encourage or allow actions leading to new business methods or activities that	Global Entrepreneurship Monitor	Country	2014

		can potentially increase personal wealth and income. Rating: 1=highly insufficient, 5=highly sufficient			
Entrepreneurship culture	Innovative and creative	Percentage of respondents that agree to: it is important to think of new ideas and be creative	European Social Survey	NUTS 2 NUTS 1 for DE, UK Missing for FRM0, ITF2, LU00, MT00, PT20, PT30	2008 - 2016
Entrepreneurship culture	Trust	Survey question on scale 0-1: Most people can be trusted	European Social Survey	NUTS 2 NUTS 1 for DE, UK Missing for FRM0, ITF2, LU00, MT00, PT20, PT30	2008 - 2016
Entrepreneurship culture robustness	Birth of new firms	Number of new firms per capita	Eurostat, OECD and national statistics offices	NUTS 2 NUTS 1 for DE and UK Country for EL	2010-2016
Networks	Innovative SMEs collaborating with others	Percentage of innovative SMEs in SME business population collaborating with others	RIS & EIS (for countries which are a NUTS 2 region) (also available in RCI)	NUTS 2 NUTS 1 for BE, UK, FR, and AT	2016
Physical Infrastructure	Accessibility via road	Population accessible within 1h30 by road, as share of the population in a neighbourhood of 120 km radius	DG Regio (RCI)	NUTS 2	2016

Physical Infrastructure	Accessibility via rail	Population accessible within 1h30 by rail (using optimal connections), as share of the population in a neighbourhood of 120 km radius	DG Regio (RCI)	NUTS 2	2014
Physical Infrastructure	Number of passenger flights	Daily number of passenger flights accessible in 90 min drive	Eurostat / Eurogeographics / National Statistical Institutes (RCI)	NUTS 2	2016
Physical Infrastructure	Household access to internet	Percentage of households with access to internet	Eurostat (RCI)	NUTS 2	2018
Finance	Venture capital	The average amount of venture capital for the last five years per capita	Invest Europe	NUTS 2	2014-2019
Finance	Credit constrained SMEs	Percentage of SMEs that is credit constrained because they either were rejected for loans or received less, or were discouraged to apply because it was too expensive or they expected to be turned down.	Investment Survey European Investment Bank	Country	2018
Leadership	The presence of actors taking a leadership role in the ecosystem	The number of coordinators on H2020 innovation projects per capita	CORDIS (Community Research and Development Information Service)	NUTS 2	2014-2019
Talent	Tertiary education	Percentage of total population that completed tertiary education	Eurostat	NUTS 2	2013

				NUTS 1 for BE, DE, and UK	
Talent	Lifelong learning	Percentage of population aged 25-64 participating in education and training	Eurostat	NUTS 2 NUTS 1 for BE, DE, and UK	2013
Talent	Business and entrepreneurship education	The extent to which training in creating or managing SMEs is incorporated within the education and training system The extent to which training in creating or managing SMEs is incorporated within the education and training system. Rating: 1=highly insufficient, 5=highly sufficient	Global Entrepreneurship Monitor	Country	2014
Talent	E-skills	Percentage of individuals in active population with high levels of e-skills	Eurostat	Country	2014
New knowledge	R&D expenditure	Intramural R&D expenditure as percentage of Gross Regional Product	Eurostat	NUTS 2	2015
Demand	Disposable income per capita	Net adjusted disposable household income in PPCS per capita (index EU average=100)	Eurostat	NUTS 2	2014
Demand	Potential market size in GRP	Index GRP PPS (EU population-weighted average=100)	Eurostat	NUTS 2	2016
Demand	Potential market size in population	Index population (EU average=100)	Eurostat	NUTS 2	2018

Intermediate services	Incubators	Percentage of incubators in total business population	Own data	NUTS 2	2019
Intermediate services	Knowledge intensive services	Percentage employment in knowledge-intensive market services	Eurostat	NUTS 2	2018
Productive entrepreneurship	Innovative new firms	Number of new firms registered in Crunchbase in the last five years per capita	Crunchbase	NUTS 2	2019
Productive entrepreneurship	High-value new firms (unicorns)	Absolute number of entrepreneurial firms valued above $1 billion founded in the last ten years	CB Insights & Dealroom	NUTS 2	2019

Appendix B

Methods

Table B1.

Correlation table

	Formal institutions	Culture	Networks	Physical infrastructure	Finance	Leadership	Talent	Knowledge	Demand	Intermediate services	EE index add	EE index log	Crunchbase output
Culture	0.781****												
Networks	0.606****	0.457****											
Physical infrastructure	0.623****	0.596****	0.520****										
Finance	0.684****	0.657****	0.531****	0.761****									
Leadership	0.302****	0.329****	0.390****	0.461****	0.420****								
Talent	0.809****	0.693****	0.686****	0.586****	0.677****	0.455****							
Knowledge	0.463****	0.465****	0.406****	0.565****	0.633****	0.581****	0.452****						
Demand	0.469****	0.453****	0.439****	0.842****	0.661****	0.345****	0.348****	0.572****					
Intermediate services	0.319****	0.359****	0.445****	0.592****	0.493****	0.653****	0.480****	0.441****	0.447****				
EE index add	0.796****	0.755****	0.729****	0.832****	0.836****	0.625****	0.802****	0.676****	0.699****	0.675****			
EE index log	0.801****	0.751****	0.709****	0.859****	0.856****	0.624****	0.805****	0.710****	0.736****	0.676****	0.985****		
Crunchbase output	0.461****	0.402****	0.469****	0.551****	0.497****	0.742****	0.617****	0.462****	0.359****	0.782****	0.696****	0.695****	
Unicorn output	0.170**	0.214***	0.127*	0.307****	0.364****	0.363****	0.269****	0.205***	0.258****	0.370****	0.351****	0.362****	0.401****

Note: *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

Figure B1.
Pairwise scatter plot of output and index with clusters of regions

Table B2.

Regression results of the additive and logarithmic index on the Crunchbase output variable including non-linear effects

	Crunchbase output			
	(1)	(2)	(3)	(4)
EE index additive	0.097***	0.013		
	(0.013)	(0.025)		
EE index additive squared		0.003***		
		(0.001)		
EE index logarithmic			0.076***	0.148***
			(0.009)	(0.024)
EE index logarithmic squared				0.006***
				(0.001)
Observations	272	272	272	272
R^2	0.378	0.415	0.283	0.385
Adjusted R^2	0.376	0.410	0.280	0.380
F Statistic	164.043*** (df = 1; 270)	95.339*** (df = 2; 269)	106.371*** (df = 1; 270)	84.062*** (df = 2; 269)

*Notes: Clustered standard errors at country level in parentheses. * p<0.05 ** p<0.01 *** p<0.001*

Table B3.

Regression results of the additive and logarithmic index on the unicorn output variable. This is an overdispersed count variable and hence we used a quasipoisson regression.

	Unicorn output	
	(1)	(2)
EE index additive	0.195***	
	(0.032)	
EE index logarithmic		0.358***
		(0.069)
Constant	-4.713***	-2.055***
	(0.645)	(0.393)
Observations	271	271
Dispersion parameter	0.959	0.924
R^2	0.240	0.274

Notes: Clustered standard errors at country level in parentheses.

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Appendix C

Index robustness

As a first robustness test we do not execute any of the modifications outlined in section 3.16. This robustness test actually results in a higher R2 of 0.62 (Table C1). However, the results are now strongly influenced by the extreme values measured in several regions that we discussed in the methodology section. Therefore, we performed a second robustness test which follows the approach outlined in the method section but instead removes those regions with a value more than four standard deviations from the mean. This concerned Inner London (as a result of a high number of incubators, leadership, and Crunchbase start-ups per population), Braunschweig (as a result of the high R&D intensity) in Germany, and Hovedstaden (as a result of leadership) in Denmark (Table C2). Since we prefer not to discard observations of which the data is reliably measured, we also performed the regression with all observations after transforming the data. We transformed the data using the Tukey transformation (Tukey, 1957) for all the variables with a huge range of variation (standard deviations above 4), instead of only the output variable as we did in the main analysis (Table C3). The result of this transformation is a distribution of data which is close to a normal distribution, thus reducing the standard deviations from the variables with extreme values. Fourth, we used a categorical approach to create each of the index elements and the output by using quantiles to give each element a score from 1-10. The index then has a minimum value of 10 and maximum value of 100 (Table C4). Furthermore, we find that many of the top performing regions are regions in which a capital city is located (see Fig. 3). To test whether the explanatory power of our index holds after controlling for the influence of capital cities on the output variable we run the regressions with a capital city indicator added, which is a dummy variable indicating whether a region contains a capital city (no = 0, yes = 1). The results are displayed in Table C5 and indeed show that capital regions perform significantly better than non-capital regions ($p<0.001$). Nevertheless, the effect of the EEI remains significant ($p<0.001$) and only shows a small decrease in coefficients.

Sixth, we also performed a regression using the principal components discussed in section 4.1. This method does not build on the assumption that all ecosystem elements have equal weights and for PC1 we find highly similar outcomes as for our index (Table C6). Finally, we perform a regression in which we control for the GRP per capita, which is one of the existing measured we compared our index with in section 4.6. The results show that the regression with the index significantly outperforms the regression with only the GRP (Table C7). It is important to note that the GRP of a region is already included in our measure for demand. Nevertheless, we found it important to test the robustness of our index when including this crucial control variable. In sum, the findings of all seven robustness tests are consistent with those presented in the main analysis, indicating the robustness of our chosen approach of calculating our index.

Table C1.

Regression with no transformation of extreme values

	Crunchbase output	
	(1)	(2)
EE index additive	0.525***	
	(0.065)	
EE index logarithmic		0.504***
		(0.100)
Constant	-4.240***	6.636***
	(0.577)	(1.175)
Observations	272	272
R^2	0.619	0.049
Adjusted R^2	0.619	0.045
F Statistic	438.82*** (df = 1; 270)	13.85*** (df = 1; 270)

Notes: Clustered standard errors at country level in parentheses.
*p<0.05; **p<0.01; ***p<0.001

Table C2.

Regression excluding observations with extreme values

	Crunchbase output	
	(1)	(2)
EE index additive	0.051***	
	(0.017)	
EE index logarithmic		0.035**
		(0.011)
Constant	-0.108	0.559 ***
	(0.115)	(0.119)
Observations	269	269
R^2	0.152	0.089
Adjusted R^2	0.149	0.086
F Statistic	47.77*** (df = 1; 267)	26.19*** (df = 1; 267)

Notes: Clustered standard errors at country level in parentheses.
*p<0.05; **p<0.01; ***p<0.001

Table C3.

Regression including Tukey transformation to variables with extreme values

	Crunchbase output	
	(1)	(2)
EE index additive	0.096***	
	(0.004)	
EE index logarithmic		0.071***
		(0.005)
Constant	-0.066	1.210***
	(0.060)	(0.052)
Observations	272	272
R^2	0.383	0.266
Adjusted R^2	0.381	0.264
F Statistic	167.87 *** (df = 1; 270)	98.03*** (df = 1; 270)

Notes: Clustered standard errors at country level in parentheses.
*p<0.05; **p<0.01; ***p<0.001

Table C4.

Regression with categorical calculation of the index

	Crunchbase output
	(1)
Categorical Index	0.092***
	(0.007)
Constant	0.471
	(0.413)
Observations	272
R^2	0.477
Adjusted R^2	0.475
F Statistic	245.98*** (df = 1; 270)

Notes: Clustered standard errors at country level in parentheses.
*p<0.05; **p<0.01; ***p<0.001

Table C5.

Regression with dummies for capital cities

	Crunchbase output	
	(1)	(2)
EE index additive	0.078***	
	(0.009)	
EE index logarithmic		0.059***
		(0.006)
Capital city	0.930**	1.141***
	(0.274)	(0.283)
Constant	0.039	1.065***
	(0.100)	(0.092)
Observations	272	272
R^2	0.456	0.410
Adjusted R^2	0.452	0.406
F Statistic	112.89*** (df = 2; 269)	93.53*** (df = 2; 269)

Notes: Clustered standard errors at country level in parentheses.
*p<0.05; **p<0.01; ***p<0.001

Table C6.

Regression with principal components

	Crunchbase output		
	(1)	(2)	(3)
Principal Component 1	0.289***	0.289***	0.289***
	(0.043)	(0.025)	(0.025)
Principal Component 2		0.394***	0.394***
		(0.001)	(0.001)
Principal Component 3			0.133***
			(0.009)
Constant	0.852***	0.852***	0.852***
	(0.092)	(0.025)	(0.025)
Observations	272	272	272
R^2	0.360	0.551	0.572
Adjusted R^2	0.357	0.548	0.567
F Statistic	151.61*** (df = 1; 270)	165.122*** (df = 2; 269)	119.46*** (df = 3; 268)

Notes: Clustered standard errors at country level in parentheses.
** p<0.05 ** p<0.01 *** p<0.001*

Table C7.

Regression with GRP as a control variable

	Crunchbase output		
	(1)	(2)	(3)
EE index additive		0.074^{***}	
		(0.018)	
EE index logarithmic			0.043^{***}
			(0.014)
GRP per capita	0.015^{***}	0.006^{**}	0.009^{***}
	(0.002)	(0.004)	(0.004)
Constant	-0.607***	-0.379	0.271
	(0.181)	(0.194)	(0.356)
Observations	273	271	271
R^2	0.281	0.400	0.326
Adjusted R^2	0.279	0.396	0.321
F Statistic	106.17^{***} (df = 1; 271)	89.362^{***} (df = 2; 268)	64.81^{***} (df = 2; 268)

Notes: Clustered standard errors at country level in parentheses.

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Appendix D

Data appendix

NUTS2 code	Crunchbase output	Formal institutions	Culture	Networks	Physical infrastructure	Finance	Leadership	Talent	Knowledge	Demand	Intermediate	EE index additive	EE index log
AT12	0.44	1.09	0.32	1.44	1.34	0.81	0.40	1.13	1.48	1.83	0.47	10.32	-1.16
AT13	3.19	1.17	0.42	1.44	1.34	3.33	5.00	2.14	1.48	1.83	3.20	21.36	5.68
AT11	0.31	1.13	0.26	1.44	0.63	1.44	0.21	0.89	0.25	1.31	0.29	7.85	-4.99
AT21	0.41	1.05	0.46	2.10	0.24	1.78	0.53	1.08	1.81	0.68	0.37	10.10	-2.18
AT22	0.85	1.11	0.34	2.10	0.36	1.82	1.33	1.01	5.00	0.81	0.69	14.57	0.66
AT31	0.83	1.08	0.28	1.55	0.50	1.26	0.34	1.05	1.86	1.10	0.39	9.41	-2.49
AT32	0.36	1.20	0.81	1.55	0.42	1.34	0.28	1.15	0.40	0.86	0.40	8.41	-3.28
AT33	0.60	1.29	0.49	1.55	0.31	1.46	0.49	1.08	1.74	0.87	0.50	9.78	-1.73
AT34	0.26	1.32	0.57	1.55	0.72	1.18	0.19	1.04	0.52	1.14	0.25	8.48	-3.53
BE10	3.09	0.35	0.25	3.19	1.61	1.87	5.00	0.74	1.89	2.36	5.00	22.26	4.22
BE24	1.11	0.61	0.35	3.19	1.61	1.37	5.00	0.54	1.89	2.36	0.89	17.81	2.78
BE31	1.71	0.41	0.43	3.19	1.61	1.33	3.28	0.44	1.89	2.36	1.54	16.48	2.47
BE21	1.39	0.61	0.42	5.00	1.96	1.37	0.52	0.54	1.84	2.36	0.63	15.24	0.95
BE22	0.82	0.61	0.32	5.00	1.07	1.37	0.25	0.54	0.35	1.97	0.37	11.85	-2.98
BE23	1.17	0.61	0.38	5.00	1.13	1.37	1.53	0.54	1.02	2.32	0.40	14.29	0.32
BE25	0.41	0.61	0.29	5.00	0.86	1.37	0.19	0.54	0.28	1.67	0.29	11.10	-4.20
BE32	0.33	0.41	0.21	2.48	0.80	1.33	0.24	0.44	0.45	1.47	0.26	8.09	-5.49
BE33	0.60	0.41	0.19	2.48	1.38	1.33	0.33	0.44	0.69	1.31	0.46	9.03	-3.85
BE34	0.32	0.41	0.16	2.48	0.53	1.33	0.19	0.44	0.21	0.79	0.42	6.97	-7.28
BE35	0.18	0.41	0.30	2.48	0.65	1.33	0.26	0.44	0.32	1.14	0.25	7.58	-5.90
BG31	0.01	0.11	0.03	0.16	0.06	0.23	0.19	0.09	0.17	0.13	0.10	1.26	-21.96
BG32	0.11	0.22	0.03	0.16	0.08	0.19	0.18	0.10	0.16	0.17	0.16	1.45	-20.66
BG33	0.36	0.18	0.04	0.16	0.12	0.17	0.20	0.12	0.14	0.14	0.25	1.51	-19.85
BG34	0.20	0.12	0.04	0.16	0.12	0.19	0.19	0.09	0.14	0.12	0.19	1.35	-20.88
BG41	1.73	0.14	0.04	0.17	0.21	0.29	0.26	0.18	0.41	0.32	1.05	3.07	-14.76
BG42	0.22	0.16	0.03	0.17	0.18	0.20	0.19	0.09	0.16	0.15	0.15	1.48	-20.24
CY00	3.03	0.23	0.19	0.79	0.46	0.51	2.31	0.34	0.16	0.25	1.66	6.89	-7.82
CZ01	2.96	0.51	0.46	0.38	0.67	1.23	0.50	0.47	1.08	0.96	3.10	9.35	-2.90
CZ02	0.16	0.40	0.31	0.38	0.67	0.58	0.23	0.26	1.08	0.96	0.36	5.23	-7.82
CZ03	0.22	0.48	0.40	0.30	0.26	0.47	0.21	0.23	0.43	0.40	0.17	3.34	-11.55
CZ04	0.09	0.33	0.27	0.31	0.28	0.47	0.18	0.19	0.14	0.55	0.18	2.90	-13.24
CZ05	0.18	0.51	0.43	0.62	0.23	0.47	0.19	0.27	0.34	0.50	0.19	3.76	-10.59
CZ06	0.60	0.56	0.32	0.30	0.33	0.58	0.29	0.30	1.36	0.49	0.38	4.91	-8.39
CZ07	0.14	0.55	0.35	0.50	0.24	0.47	0.19	0.22	0.33	0.49	0.16	3.49	-11.36
CZ08	0.27	0.48	0.30	0.40	0.33	0.56	0.19	0.23	0.30	0.61	0.18	3.58	-11.09
DE30	5.00	1.20	1.20	0.60	3.04	5.00	0.88	0.84	1.44	1.67	5.00	20.89	4.78
DE40	0.45	1.29	0.76	0.60	3.04	1.95	0.30	0.52	1.44	1.67	0.26	11.84	-1.08
DE11	0.60	1.54	1.54	0.39	1.02	1.39	0.27	0.64	5.00	2.64	0.33	14.76	-0.02
DE12	0.79	1.54	1.54	0.35	2.05	1.39	0.75	0.64	5.00	2.62	0.24	16.10	1.24
DE13	0.33	1.54	1.54	0.33	0.85	1.39	0.33	0.64	1.16	1.91	0.18	9.87	-2.53
DE14	0.29	1.54	1.54	0.43	0.56	1.39	0.32	0.64	5.00	2.07	0.17	13.66	-1.23
DE21	2.18	1.77	1.21	0.36	2.06	2.47	3.77	0.58	5.00	2.59	1.45	21.26	5.09
DE22	0.22	1.77	1.21	0.17	0.77	2.47	0.20	0.58	0.32	1.29	0.17	8.94	-5.22

NUTS2 code	Crunchbase output	Formal institutions	Culture	Networks	Physical infrastructure	Finance	Leadership	Talent	Knowledge	Demand	Intermediate	EE index additive	EE index log
DE23	0.27	1.77	1.21	0.23	0.82	2.47	0.26	0.58	0.64	1.18	0.19	9.35	-3.84
DE24	0.30	1.77	1.21	0.31	0.64	2.47	0.26	0.58	0.60	1.34	0.14	9.33	-4.03
DE25	0.40	1.77	1.21	0.31	1.37	2.47	0.37	0.58	3.29	1.74	0.32	13.43	-0.12
DE26	0.31	1.77	1.21	0.38	0.92	2.47	0.27	0.58	0.70	1.64	0.23	10.17	-2.56
DE27	0.45	1.77	1.21	0.48	1.13	2.47	0.21	0.58	0.43	1.81	0.20	10.30	-2.92
DE50	0.60	1.55	1.31	0.41	0.93	0.75	0.80	0.56	1.30	1.42	0.46	9.49	-1.52
DE60	3.19	1.68	0.92	0.29	2.18	2.94	0.53	0.74	0.79	2.70	2.79	15.56	1.92
DE71	0.97	1.53	1.40	0.35	2.73	1.28	0.31	0.61	1.82	2.72	1.14	13.89	1.04
DE72	0.20	1.53	1.40	0.40	1.31	1.28	0.23	0.61	1.06	1.74	0.22	9.78	-2.50
DE73	0.29	1.53	1.40	0.25	0.69	1.28	0.20	0.61	0.43	1.21	0.21	7.80	-5.07
DE80	0.27	1.61	0.87	0.37	0.49	0.93	0.26	0.48	0.57	0.52	0.18	6.28	-6.43
DE91	0.23	1.68	1.03	0.29	0.71	0.73	0.41	0.46	5.00	1.32	0.25	11.88	-2.51
DE92	0.53	1.68	1.03	0.52	1.03	0.73	0.26	0.46	0.93	1.57	0.24	8.45	-3.55
DE93	0.19	1.68	1.03	0.37	0.82	0.73	0.20	0.46	0.24	1.54	0.24	7.31	-5.77
DE94	0.24	1.68	1.03	0.34	0.72	0.73	0.21	0.46	0.24	1.25	0.20	6.85	-6.34
DEA1	0.51	1.30	1.03	0.29	2.39	1.27	0.23	0.48	0.51	3.37	0.44	11.30	-2.32
DEA2	0.88	1.30	1.03	0.50	2.19	1.27	0.56	0.48	1.34	2.92	0.67	12.24	0.25
DEA3	0.38	1.30	1.03	0.56	1.53	1.27	0.23	0.48	0.28	2.34	0.21	9.23	-3.80
DEA4	0.34	1.30	1.03	0.39	0.94	1.27	0.22	0.48	0.56	1.89	0.20	8.28	-4.25
DEA5	0.41	1.30	1.03	0.54	1.80	1.27	0.24	0.48	0.46	2.39	0.23	9.73	-3.04
DEB1	0.37	1.58	1.28	0.34	1.56	1.77	0.19	0.52	0.19	2.11	0.21	9.74	-4.18
DEB2	0.18	1.58	1.28	0.53	0.59	1.77	0.21	0.52	1.50	1.42	0.18	9.57	-3.08
DEB3	0.40	1.58	1.28	0.36	1.90	1.77	0.33	0.52	2.15	2.27	0.27	12.42	-0.61
DEC0	0.42	1.50	0.88	0.56	0.86	0.98	0.26	0.41	0.42	1.45	0.20	7.52	-4.83
DED2	0.42	1.34	1.32	0.63	0.61	1.57	0.49	0.60	3.94	0.99	0.34	11.84	-0.87
DED4	0.24	1.34	1.32	1.34	0.57	1.57	0.21	0.60	0.52	1.11	0.16	8.74	-3.73
DED5	0.92	1.34	1.32	0.93	1.18	1.57	0.37	0.60	0.66	1.10	0.60	9.68	-1.22
DEE0	0.40	1.19	0.62	0.66	0.93	0.99	0.22	0.48	0.36	0.87	0.17	6.49	-5.96
DEF0	0.27	1.56	0.90	0.44	0.96	0.90	0.26	0.47	0.39	1.41	0.33	7.62	-4.43
DEG0	0.33	1.44	0.89	0.44	0.58	1.26	0.28	0.56	0.64	0.93	0.18	7.20	-4.96
DK01	5.00	2.98	5.00	0.63	4.68	2.11	5.00	5.00	5.00	0.90	3.78	35.08	10.58
DK02	0.47	2.81	3.48	0.60	1.18	1.88	0.28	4.76	0.29	0.58	0.36	16.22	0.03
DK03	1.13	3.01	3.90	0.74	0.56	0.44	0.40	5.00	0.60	0.42	0.35	15.40	-1.01
DK04	1.73	3.50	3.89	0.58	0.58	0.99	1.90	5.00	1.10	0.42	0.45	18.40	2.19
DK05	1.06	2.99	3.75	0.50	0.55	0.91	0.73	4.05	0.40	0.29	0.37	14.54	-1.03
EE00	5.00	0.93	0.69	0.66	0.41	1.01	1.34	1.65	0.40	0.10	0.76	7.96	-4.39
EL30	0.76	0.13	0.34	0.94	0.65	0.10	0.34	0.37	0.29	0.93	1.51	5.60	-8.87
EL41	0.31	0.11	0.48	0.64	0.19	0.05	1.56	0.23	0.20	0.03	0.35	3.85	-15.07
EL42	0.34	0.11	0.79	0.33	0.17	0.05	0.19	0.17	0.12	0.09	0.32	2.35	-17.30
EL43	0.23	0.11	0.47	1.59	0.13	0.07	0.28	0.20	0.42	0.11	0.20	3.58	-14.80
EL51	0.12	0.10	0.51	0.56	0.12	0.06	4.70	0.20	0.19	0.12	0.29	6.85	-13.58
EL52	0.32	0.10	0.27	0.63	0.18	0.12	1.20	0.25	0.22	0.27	0.31	3.57	-13.03
EL53	0.01	0.10	0.13	1.14	0.11	0.05	0.19	0.22	0.15	0.15	0.12	2.37	-18.41
EL54	0.28	0.10	0.13	0.26	0.10	0.06	0.26	0.22	0.31	0.11	0.23	1.78	-18.53
EL61	0.22	0.13	0.45	0.58	0.11	0.06	0.23	0.24	0.19	0.17	0.23	2.39	-16.18
EL62	0.30	0.13	0.14	0.43	0.17	0.05	0.20	0.17	0.16	0.09	0.21	1.75	-18.76

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EL63	0.19	0.13	0.28	0.58	0.10	0.05	0.32	0.21	0.34	0.14	0.13	2.27	-16.96
EL64	0.21	0.13	0.26	0.41	0.12	0.07	0.19	0.17	0.17	0.31	0.25	2.09	-16.77
EL65	0.12	0.13	0.21	0.32	0.15	0.06	0.18	0.18	0.15	0.17	0.21	1.75	-18.16
ES11	0.53	0.33	0.29	0.40	0.35	0.77	0.29	0.68	0.23	0.35	0.43	4.13	-9.54
ES12	0.61	0.46	0.16	0.36	0.41	0.71	0.55	0.77	0.20	0.35	0.38	4.37	-9.29
ES13	0.28	0.52	0.80	0.24	0.44	0.41	0.35	0.76	0.22	0.38	0.26	4.38	-9.17
ES21	0.85	0.58	0.44	0.70	0.58	1.03	4.63	1.19	0.59	1.06	0.57	11.37	-1.56
ES22	0.70	0.54	0.45	0.35	0.42	1.67	1.90	0.99	0.45	0.64	0.53	7.94	-4.06
ES23	0.73	0.47	0.86	0.29	0.32	0.44	1.25	0.80	0.23	0.37	0.15	5.18	-8.45
ES24	0.46	0.44	0.26	0.25	1.08	0.49	0.95	0.77	0.23	0.28	0.29	5.04	-8.47
ES30	2.18	0.37	0.92	0.26	3.21	1.90	2.11	1.19	0.49	2.05	1.97	14.45	0.97
ES41	0.40	0.35	0.45	0.24	0.44	0.92	0.32	0.74	0.25	0.28	0.22	4.21	-9.77
ES42	0.18	0.35	0.41	0.25	0.75	0.67	0.20	0.57	0.17	0.31	0.18	3.85	-10.90
ES43	0.26	0.42	0.32	0.24	0.27	0.70	0.25	0.53	0.19	0.13	0.16	3.20	-12.65
ES51	2.06	0.34	0.64	0.26	1.30	2.01	2.46	0.71	0.41	0.87	1.20	10.21	-2.22
ES52	0.86	0.33	0.38	0.24	0.60	0.69	0.48	0.70	0.26	0.53	0.43	4.64	-8.30
ES53	0.65	0.31	0.37	0.13	0.62	1.43	0.23	0.52	0.14	0.32	0.38	4.45	-10.53
ES61	0.45	0.28	0.39	0.23	0.38	0.44	0.30	0.54	0.26	0.31	0.25	3.38	-11.21
ES62	0.40	0.39	0.28	0.21	0.56	0.63	0.35	0.56	0.22	0.40	0.31	3.91	-10.04
ES70	0.41	0.29	0.33	0.17	0.49	0.37	0.25	0.54	0.16	0.21	0.26	3.07	-12.55
FI19	1.20	1.88	2.86	0.95	0.41	1.27	0.52	3.13	1.42	0.17	0.33	12.94	-1.09
FI1B	5.00	2.05	3.05	0.89	1.55	3.13	5.00	5.00	2.76	0.75	5.00	29.18	8.85
FI1C	1.18	1.95	2.28	1.23	0.64	1.23	0.37	2.98	0.64	0.27	0.65	12.24	-0.62
FI1D	1.08	1.99	2.41	0.78	0.30	1.33	0.59	2.92	1.04	0.05	0.40	11.81	-2.87
FI20	0.72	3.16	2.43	NA	NA	NA	0.18	3.06	0.13	0.07	4.83	NA	NA
FR10	3.05	0.64	0.68	0.77	5.00	2.96	2.64	1.95	1.48	3.58	3.32	23.03	6.12
FRB0	0.36	0.61	0.87	0.47	0.71	0.72	0.21	1.13	0.46	0.74	0.18	6.10	-6.30
FRC1	0.37	0.57	0.66	0.47	0.41	0.54	0.21	1.10	0.25	0.49	0.20	4.90	-8.40
FRC2	0.31	0.54	1.03	0.47	0.26	0.55	0.22	1.19	1.25	0.63	0.22	6.38	-6.32
FRD1	0.26	0.61	0.84	0.47	0.33	0.62	0.22	0.87	0.33	0.52	0.22	5.01	-7.99
FRD2	0.30	0.63	0.68	0.47	0.85	0.73	0.19	1.09	0.38	1.01	0.29	6.31	-5.87
FRE1	0.46	0.58	0.75	0.54	0.98	1.00	0.21	1.22	0.23	1.02	0.25	6.79	-5.64
FRE2	0.25	0.61	0.58	0.54	1.24	0.67	0.21	0.77	0.37	1.25	0.39	6.63	-5.36
FRF1	0.45	0.60	0.48	0.48	0.72	1.03	0.33	1.32	0.49	1.20	0.20	6.84	-5.28
FRF2	0.32	0.59	1.19	0.48	0.97	0.75	0.19	0.84	0.20	0.47	0.19	5.87	-7.28
FRF3	0.37	0.56	0.85	0.48	0.47	0.83	0.18	1.08	0.32	0.76	0.16	5.68	-7.32
FRG0	0.46	0.72	0.89	0.64	0.50	0.85	0.22	1.44	0.31	0.68	0.32	6.56	-5.62
FRH0	0.44	0.74	0.57	0.64	0.36	1.19	0.25	1.65	0.64	0.57	0.25	6.86	-5.42
FRI1	0.59	0.71	0.80	0.68	0.52	0.93	0.26	1.42	0.44	0.53	0.29	6.59	-5.35
FRI2	0.27	0.68	0.73	0.68	0.17	0.54	0.22	1.39	0.25	0.37	0.19	5.24	-8.66
FRI3	0.28	0.58	0.48	0.68	0.35	0.44	0.19	1.03	0.24	0.51	0.21	4.71	-8.83
FRJ1	0.53	0.53	0.76	0.57	0.53	1.08	0.22	1.26	0.92	0.51	0.30	6.67	-5.30
FRJ2	0.58	0.62	0.63	0.57	0.46	1.55	0.35	2.45	5.00	0.51	0.82	12.96	-1.26
FRK1	0.44	0.62	0.87	0.77	0.34	0.91	0.21	1.06	0.80	0.49	0.13	6.21	-6.51
FRK2	0.68	0.67	0.81	0.77	0.60	1.57	0.31	2.09	1.31	0.95	0.32	9.39	-2.31
FRL0	0.71	0.55	0.83	0.45	0.75	1.24	0.25	1.40	1.01	0.75	0.51	7.74	-3.68

NUTS2 code	Crunchbase output	Formal institutions	Culture	Networks	Physical infrastructure	Finance	Leadership	Talent	Knowledge	Demand	Intermediate	EE index additive	EE index log
FRM0	0.50	0.51	1.00	0.45	0.24	1.56	0.18	0.80	0.13	0.14	0.53	5.55	-9.00
HR03	0.47	0.16	0.07	0.22	0.22	0.12	0.21	0.15	0.14	0.12	0.42	1.82	-18.09
HR04	0.47	0.16	0.10	0.29	0.22	0.15	0.22	0.14	0.27	0.24	0.28	2.08	-16.23
HU11	2.00	0.14	0.24	0.32	0.69	0.82	0.69	0.46	0.57	0.73	3.86	8.52	-5.78
HU12	0.27	0.14	0.24	0.32	0.69	0.82	0.20	0.46	0.57	0.73	0.25	4.41	-9.78
HU21	0.36	0.18	0.16	0.22	0.34	0.50	0.22	0.24	0.24	0.46	0.14	2.71	-13.92
HU22	0.25	0.18	0.18	0.26	0.31	0.48	0.21	0.25	0.17	0.38	0.13	2.55	-14.41
HU23	0.24	0.18	0.35	0.21	0.15	0.52	0.18	0.25	0.15	0.22	0.13	2.34	-15.45
HU31	0.21	0.17	0.15	0.25	0.16	0.44	0.20	0.24	0.16	0.33	0.14	2.24	-15.65
HU32	0.36	0.16	0.16	0.18	0.14	0.60	0.20	0.26	0.28	0.26	0.12	2.35	-15.61
HU33	0.30	0.21	0.14	0.25	0.17	0.50	0.22	0.25	0.46	0.25	0.14	2.57	-14.49
IE04	1.46	1.67	1.06	0.63	0.18	1.27	1.43	0.62	0.57	0.20	0.32	7.96	-4.76
IE05	1.43	1.60	1.08	0.69	0.29	0.70	0.97	0.89	0.28	0.37	0.65	7.52	-4.26
IE06	5.00	1.60	0.79	0.68	0.88	1.95	3.97	0.89	0.30	0.66	3.58	15.28	1.28
ITC1	0.49	0.17	0.34	0.39	0.80	0.37	0.38	0.18	0.74	1.25	0.54	5.15	-8.38
ITC2	0.01	0.23	0.37	0.20	0.24	0.28	0.25	0.18	0.19	0.77	0.32	3.02	-12.96
ITC3	0.38	0.17	0.17	0.22	0.66	0.34	0.83	0.21	0.38	0.86	0.77	4.62	-9.65
ITC4	0.89	0.25	0.40	0.27	0.76	0.78	0.48	0.20	0.32	2.07	1.14	6.67	-6.74
ITF1	0.29	0.12	0.27	0.28	0.27	0.46	0.22	0.19	0.24	0.58	0.47	3.10	-12.71
ITF2	0.24	0.17	0.14	0.27	0.13	0.28	0.21	0.18	0.19	0.50	0.32	2.39	-15.17
ITF3	0.22	0.12	0.41	0.17	0.38	0.41	0.23	0.16	0.32	0.68	0.49	3.37	-12.19
ITF4	0.22	0.14	0.57	0.29	0.30	0.43	0.21	0.16	0.25	0.42	0.36	3.14	-12.45
ITF5	0.38	0.14	0.70	0.16	0.18	0.30	0.21	0.17	0.18	0.34	0.36	2.73	-14.26
ITF6	0.20	0.10	0.60	0.26	0.21	0.30	0.21	0.17	0.19	0.27	0.32	2.64	-14.32
ITG1	0.15	0.14	0.20	0.22	0.27	0.29	0.19	0.15	0.25	0.38	0.34	2.42	-14.65
ITG2	0.43	0.17	0.19	0.60	0.30	0.71	0.21	0.18	0.21	0.23	0.35	3.15	-12.83
ITH1	0.33	0.27	0.67	0.28	0.17	0.28	0.44	0.22	0.20	0.77	0.19	3.49	-11.88
ITH2	1.17	0.27	1.91	0.45	0.21	0.28	5.00	0.24	0.53	1.02	0.42	10.33	-5.59
ITH3	0.40	0.26	0.49	0.24	0.51	0.34	0.37	0.18	0.28	1.25	0.42	4.34	-9.86
ITH4	0.50	0.25	0.44	0.30	0.37	0.61	0.41	0.22	0.42	0.82	0.32	4.19	-9.45
ITH5	0.46	0.26	0.43	0.22	0.53	0.45	0.58	0.21	0.53	1.41	0.37	4.99	-8.53
ITI1	0.40	0.21	0.40	0.26	0.39	0.53	0.43	0.20	0.34	0.87	0.47	4.11	-9.82
ITI2	0.35	0.15	0.25	0.27	0.25	0.37	0.33	0.23	0.25	0.68	0.39	3.17	-12.31
ITI3	0.28	0.16	0.40	0.28	0.41	0.51	0.25	0.21	0.22	0.68	0.35	3.47	-11.49
ITI4	0.65	0.15	0.50	0.42	0.89	0.40	0.85	0.24	0.44	1.16	0.66	5.72	-7.17
LT01	3.87	0.55	0.28	1.71	0.28	0.10	0.54	1.09	0.26	0.28	4.99	10.09	-6.41
LT02	0.39	0.55	0.28	0.87	0.19	0.10	0.22	1.09	0.26	0.19	0.18	3.95	-12.02
LU00	4.47	0.54	1.26	0.50	0.70	2.26	1.16	2.69	0.33	1.91	1.73	13.08	0.60
LV00	1.33	0.61	0.52	0.15	0.23	0.10	0.27	0.83	0.18	0.11	0.41	3.41	-13.16
MT00	4.59	0.19	0.04	0.20	0.42	0.39	0.58	0.19	0.21	0.25	2.23	4.69	-12.60
NL23	1.22	1.18	3.90	0.99	2.81	1.07	0.23	1.22	0.48	1.81	1.09	14.79	1.30
NL32	5.00	1.05	5.00	0.99	2.81	3.02	3.08	1.92	0.48	1.81	5.00	25.16	7.03
NL11	1.20	1.19	4.68	1.41	0.87	1.39	4.47	1.38	0.69	0.73	0.73	17.53	3.06
NL12	0.54	1.19	3.92	0.89	1.13	0.99	0.23	1.01	0.22	0.73	0.56	10.86	-2.34
NL13	0.38	1.19	3.67	1.45	0.79	1.43	0.20	1.06	0.21	0.89	0.69	11.59	-1.63
NL21	1.16	1.18	4.29	1.03	1.57	1.66	0.65	1.24	0.56	1.16	0.51	13.86	1.30

NUTS2 code	Crunchbase output	Formal institutions	Culture	Networks	Physical infrastructure	Finance	Leadership	Talent	Knowledge	Demand	Intermediate	EE index additive	EE index log
NL22	0.73	1.18	5.00	1.10	2.83	1.62	1.24	1.41	0.74	1.69	0.85	17.67	4.02
NL31	2.33	1.05	4.19	1.37	3.58	2.84	5.00	2.29	0.79	2.32	1.77	25.18	7.72
NL33	1.80	1.05	4.50	1.15	3.02	2.09	2.62	1.43	0.75	2.03	2.78	21.43	6.30
NL34	0.36	1.05	4.35	1.21	1.03	1.45	0.19	0.98	0.17	1.56	0.53	12.52	-1.51
NL41	1.17	1.12	4.80	1.08	3.13	1.69	0.65	1.33	1.26	1.93	1.48	18.46	4.55
NL42	0.69	1.12	5.00	1.05	2.07	1.59	0.72	1.01	0.56	1.81	0.86	15.80	2.51
PL21	0.67	0.44	0.28	0.17	0.22	0.25	0.21	0.22	0.40	0.59	0.21	3.01	-12.79
PL22	0.19	0.43	0.33	0.20	0.29	0.19	0.19	0.20	0.18	0.88	0.22	3.11	-13.09
PL41	0.40	0.43	0.21	0.16	0.25	0.19	0.20	0.20	0.20	0.45	0.17	2.46	-14.71
PL42	0.31	0.45	0.38	0.17	0.29	0.20	0.20	0.19	0.14	0.26	0.22	2.50	-14.49
PL43	0.10	0.44	0.30	0.15	0.23	0.16	0.18	0.18	0.12	0.31	0.16	2.23	-15.75
PL51	0.54	0.43	0.35	0.17	0.23	0.19	0.21	0.23	0.22	0.51	0.24	2.77	-13.46
PL52	0.13	0.47	0.49	0.19	0.21	0.15	0.19	0.18	0.14	0.48	0.18	2.67	-14.39
PL61	0.17	0.46	0.33	0.18	0.25	0.16	0.19	0.17	0.15	0.37	0.18	2.45	-14.81
PL62	0.20	0.46	0.16	0.17	0.22	0.22	0.19	0.18	0.14	0.21	0.13	2.07	-16.43
PL63	0.50	0.51	0.41	0.17	0.39	0.19	0.20	0.23	0.28	0.34	0.40	3.13	-12.27
PL71	0.21	0.39	0.18	0.15	0.28	0.19	0.19	0.20	0.19	0.52	0.24	2.52	-14.53
PL72	0.14	0.42	0.44	0.18	0.14	0.15	0.20	0.20	0.18	0.38	0.12	2.41	-15.32
PL81	0.19	0.39	0.28	0.18	0.17	0.16	0.20	0.23	0.27	0.27	0.14	2.28	-15.24
PL82	0.20	0.40	0.35	0.20	0.18	0.15	0.19	0.18	0.33	0.29	0.16	2.43	-14.73
PL84	0.21	0.43	0.42	0.18	0.20	0.16	0.19	0.22	0.20	0.19	0.13	2.31	-15.39
PL91	1.89	0.42	0.38	0.18	0.63	0.35	0.35	0.35	0.50	0.99	1.88	6.05	-7.18
PL92	0.16	0.42	0.38	0.18	0.28	0.35	0.18	0.35	0.50	0.59	0.16	3.40	-11.68
PT11	0.51	0.52	0.24	0.26	0.32	0.41	0.38	0.66	0.35	0.40	0.21	3.75	-10.36
PT15	0.64	0.46	0.24	0.14	0.38	0.21	0.27	0.69	0.14	0.21	0.23	2.96	-13.41
PT16	1.22	0.55	0.22	0.42	0.26	0.41	0.42	0.73	0.31	0.33	0.22	3.86	-10.22
PT17	2.00	0.56	0.43	0.34	1.29	0.62	0.80	1.17	0.41	1.05	3.74	10.41	-2.30
PT18	0.40	0.61	0.28	0.30	0.17	0.25	0.34	0.63	0.16	0.25	0.14	3.13	-12.84
PT20	0.27	0.54	0.59	0.16	0.39	0.28	0.18	0.50	0.14	0.04	0.23	3.05	-14.18
PT30	0.67	0.58	0.59	0.21	0.36	0.33	0.29	0.64	0.14	0.13	0.18	3.45	-12.16
RO11	0.60	0.13	0.46	0.14	0.15	0.10	0.20	0.08	0.15	0.22	0.17	1.80	-18.35
RO12	0.28	0.16	0.27	0.14	0.10	0.10	0.18	0.08	0.14	0.22	0.13	1.52	-19.49
RO21	0.27	0.14	0.23	0.12	0.10	0.10	0.19	0.07	0.15	0.17	0.08	1.36	-20.60
RO22	0.12	0.12	0.30	0.15	0.10	0.10	0.19	0.07	0.11	0.19	0.19	1.51	-19.69
RO31	0.13	0.19	0.28	0.14	0.15	0.14	0.19	0.07	0.14	0.35	0.21	1.84	-17.74
RO32	1.22	0.14	0.27	0.16	0.55	0.14	0.26	0.15	0.23	1.91	1.71	5.53	-11.14
RO41	0.12	0.14	0.37	0.12	0.12	0.13	0.18	0.08	0.12	0.18	0.10	1.54	-19.62
RO42	0.33	0.16	0.54	0.13	0.16	0.10	0.19	0.07	0.15	0.21	0.15	1.87	-18.22
SE11	5.00	2.34	3.88	0.46	1.66	4.59	2.22	4.33	3.34	1.26	5.00	29.08	8.78
SE12	0.82	2.34	2.50	0.80	0.62	1.77	0.96	2.69	3.77	0.42	1.13	17.01	3.17
SE21	0.47	2.37	3.35	0.72	0.36	1.03	0.23	1.92	0.41	0.20	0.54	11.13	-3.16
SE22	1.73	2.37	3.04	0.38	1.07	2.44	1.13	2.99	2.04	0.63	3.03	19.11	4.53
SE23	1.15	2.37	2.80	0.39	0.61	1.83	0.89	3.14	3.43	0.43	1.51	17.40	2.89
SE31	0.40	2.18	2.65	1.32	0.32	0.97	0.24	1.50	0.34	0.12	0.44	10.07	-4.18
SE32	0.82	2.18	2.41	0.74	0.32	1.21	0.18	1.80	0.20	0.05	0.37	9.47	-6.34
SE33	0.83	2.18	3.73	0.68	0.29	1.54	0.66	2.19	1.22	0.03	0.32	12.84	-3.13

NUTS2 code	Crunchbase output	Formal institutions	Culture	Networks	Physical infrastructure	Finance	Leadership	Talent	Knowledge	Demand	Intermediate	EE index additive	EE index log
SI03	0.37	0.31	0.31	0.52	0.29	0.32	0.26	0.35	0.45	0.47	0.18	3.47	-11.00
SI04	1.52	0.31	0.37	0.71	0.47	0.51	2.09	0.53	1.17	0.51	0.67	7.34	-4.75
SK01	2.43	0.24	0.67	0.51	0.72	1.06	0.62	0.77	0.55	1.25	1.32	7.70	-3.62
SK02	0.15	0.23	0.25	0.23	0.19	0.40	0.20	0.29	0.23	0.52	0.16	2.69	-13.73
SK03	0.16	0.28	0.33	0.35	0.11	0.32	0.19	0.31	0.29	0.39	0.14	2.71	-13.75
SK04	0.23	0.28	0.26	0.33	0.12	0.36	0.19	0.31	0.20	0.30	0.14	2.51	-14.41
UKH2	1.15	2.26	1.23	2.27	5.00	2.03	0.27	1.65	0.34	4.76	0.76	20.57	3.55
UKH3	0.56	2.26	1.23	2.27	5.00	2.03	0.23	1.65	0.34	4.76	0.63	20.40	3.21
UKI3&4	5.00	2.18	1.74	2.27	5.00	3.66	5.00	3.18	0.34	4.76	5.00	33.13	9.92
UKI5	0.29	2.18	1.74	2.27	5.00	3.66	0.21	3.18	0.34	4.76	1.49	24.83	5.55
UKI6	0.47	2.18	1.74	2.27	5.00	3.66	0.20	3.18	0.34	4.76	2.86	26.20	6.15
UKI7	0.72	2.18	1.74	2.27	5.00	3.66	0.24	3.18	0.34	4.76	2.35	25.72	6.11
UKC1	0.64	2.33	1.07	3.56	0.57	0.87	0.38	1.21	0.25	0.83	0.30	11.36	-2.09
UKC2	1.23	2.33	1.07	3.56	0.64	0.87	0.50	1.21	0.32	0.62	0.43	11.54	-1.39
UKD1	0.75	1.91	1.13	1.90	0.38	0.93	0.18	1.53	0.31	0.59	0.49	9.36	-3.31
UKD3	1.85	1.91	1.13	1.90	1.42	0.93	0.46	1.53	0.24	1.91	0.97	12.40	0.54
UKD4	0.69	1.91	1.13	1.90	1.01	0.93	0.29	1.53	0.23	1.50	0.25	10.68	-1.89
UKD6	1.38	1.91	1.13	1.90	1.35	0.93	0.24	1.53	4.19	2.29	1.15	16.63	3.06
UKD7	0.75	1.91	1.13	1.90	1.59	0.93	0.39	1.53	0.43	1.64	0.33	11.79	-0.16
UKE1	0.51	2.09	0.71	4.75	0.62	0.76	0.22	1.40	0.21	0.87	0.22	11.85	-3.21
UKE2	1.17	2.09	0.71	4.75	0.70	0.76	0.66	1.40	0.45	1.30	0.46	13.28	-0.08
UKE3	0.79	2.09	0.71	4.75	1.16	0.76	0.69	1.40	0.32	1.59	0.29	13.77	-0.11
UKE4	0.93	2.09	0.71	4.75	1.22	0.76	0.55	1.40	0.26	1.67	0.47	13.88	0.03
UKF1	0.75	2.06	1.01	3.81	0.97	0.66	0.48	1.47	1.25	1.67	0.37	13.77	1.04
UKF2	0.92	2.06	1.01	3.81	1.47	0.66	0.29	1.47	0.30	1.66	0.55	13.28	-0.13
UKF3	0.71	2.06	1.01	3.81	0.39	0.66	0.26	1.47	0.14	0.97	0.26	11.04	-3.58
UKG1	0.85	2.33	0.93	2.94	1.47	1.09	0.24	1.29	2.04	1.73	0.69	14.72	2.00
UKG2	0.68	2.33	0.93	2.94	1.17	1.09	0.21	1.29	0.18	1.54	0.29	11.96	-1.72
UKG3	1.07	2.33	0.93	2.94	2.37	1.09	2.20	1.29	0.57	1.54	0.82	16.07	3.51
UKH1	1.99	2.26	1.23	1.97	0.69	2.03	5.00	1.65	5.00	1.08	0.70	21.62	5.49
UKJ1	2.53	2.21	1.25	3.66	3.55	1.37	4.80	2.24	2.81	3.14	1.64	26.68	8.95
UKJ2	1.49	2.21	1.25	3.66	4.66	1.37	0.37	2.24	0.43	3.51	1.18	20.88	4.55
UKJ3	1.10	2.21	1.25	3.66	2.33	1.37	0.41	2.24	0.73	1.95	0.71	16.87	3.42
UKJ4	0.83	2.21	1.25	3.66	4.96	1.37	0.26	2.24	0.32	2.34	0.53	19.15	2.77
UKK1	1.87	2.32	0.90	1.45	1.18	1.30	1.00	1.96	0.69	1.53	0.73	13.05	1.94
UKK2	0.99	2.32	0.90	1.45	0.56	1.30	0.27	1.96	0.22	1.10	0.46	10.54	-2.03
UKK3	0.84	2.32	0.90	1.45	0.54	1.30	0.18	1.96	0.15	0.37	0.58	9.74	-3.75
UKK4	0.91	2.32	0.90	1.45	0.58	1.30	1.11	1.96	0.28	0.63	0.40	10.92	-1.04
UKL1	0.48	2.23	1.20	2.50	0.55	0.95	0.26	1.65	0.21	0.51	0.27	10.34	-3.11
UKL2	1.55	2.23	1.20	2.50	0.77	0.95	0.48	1.65	0.30	0.87	0.57	11.53	-0.54
UKM5	1.26	2.15	1.17	3.29	0.47	0.79	0.39	2.11	0.37	0.49	1.83	13.04	-0.20
UKM6	0.61	2.15	1.17	3.29	0.26	0.79	0.25	2.11	0.16	0.14	0.13	10.45	-5.94
UKM7	1.78	2.15	1.17	3.29	1.13	0.79	2.68	2.11	0.71	0.78	0.60	15.40	2.63
UKM8	1.33	2.15	1.17	3.29	3.84	0.79	0.96	2.11	0.28	1.02	0.61	16.21	2.18
UKM9	0.36	2.15	1.17	3.29	1.16	0.79	0.19	2.11	0.32	0.60	0.20	11.97	-2.17
UKN0	0.87	1.72	0.96	2.93	0.68	0.74	0.32	1.21	0.45	0.47	0.45	9.94	-2.40