Master Thesis – master Innovation Sciences

Connected Ecosystems:

A Quantitative Analysis of Spillover Effects in Neighbouring Entrepreneurial Ecosystems

Date	30-06-2023
Candidate	BSc. Brendan Oostveen
Supervisor	Dr. Frank van Rijnsoever
Second supervisor	MSc. Jip Leendertse
Second reader	Dr. Janpieter van der Pol

Utrecht University

Abstract

Innovative entrepreneurship is an important driver of social and economic progress. To gain more understanding on spatial variation and distribution of innovative entrepreneurship, we[1] have analysed the role of spillover effects in Entrepreneurial Ecosystems (EEs). Drawing on the conceptual frameworks of Entrepreneurial Ecosystem theory and resource mobility theory, the relationship between neighbouring EE-elements and their effect on focal regions is revealed, providing new insights for academic research and policy design. Previous literature suggests that resources for entrepreneurship are mobile and can be transferred over geographical distances, due to infrastructure, networks and globalisation. Thereby potentially benefiting nearby regions. Adding this logic to EE literature creates a framework where 'mobile' EE-elements create externalities for neighbouring regions. Thus, enabling an answer to the potential effects neighbouring regions might have on a focal region. Employing a quantitative research design, we conduct spatial regression analyses on 259 European NUTS 2 regions, using seven EE-elements as the independent variables. Using and expanding an existing dataset on EE-elements gave the opportunity to identify the spillover effects, which lead to an answer to the seven hypotheses. The results reveal a counter-intuitive message to what was expected: innovative entrepreneurship output tends to suffer in regions neighbouring high-performing EEs. The effects of six elements, thus excluding the seventh 'Leadership', suggest a form of drain rather than beneficial spillovers. The findings remain robust even after various robustness checks. These results present a contrary image compared to the prevailing theory, instigating new thoughts for future assessment of EEs. Considering these findings, policymakers and ecosystem stakeholders may need to adapt their strategies, laying their focus on local EE development incorporating the potential negative effects of well-performing neighbouring regions. Despite certain limitations, such as data availability and measurement challenges, this study provides pivotal insights into the not-so-positive interregional influences in EEs and strengthens the foundation for quantitative research in this field. This study serves as a beginning for future research, which can focus on diverse geographical levels, over time, aimed at diving deeper into the dynamics of entrepreneurial ecosystems, the ten elements, and their impact on innovative entrepreneurial activity.

[1] Due to common academic writing courtesy, the plural of 'we' is utilized even though there is a single author.

Contents

1. Introduction

Entrepreneurship is important for social and economic progress (Audretsch et al., 2006; World Economic Forum, 2014). Countries and regions stimulate the creation of new innovative firms through various policy measures (Isenberg, 2011; OECD, 2009). However, in practice, large differences in entrepreneurial activity exist between regions (Brown & Mason, 2017). To understand these differences, researchers have increasingly focused on analysing and explaining entrepreneurial enabling factors, mainly within a specific regional context (See for example, Acs et al., 2017; Leendertse et al., 2022; Stam, 2015; Stam & van de Ven, 2021). However, Tobler's theory of: "*All Things Are Related, But Nearby Things Are More Related Than Distant Things"* presents some considerations about interregional effects (Tobler, 1970). This theory underscores a need for examining the effects that may exist between regions, and thus improving the overall understanding of regional entrepreneurial activity.

A prominent approach to explain spatial occurrence of entrepreneurial activity is the concept of entrepreneurial ecosystems (EEs), which is an attempt to capture all different factors in a certain region that, combined, enable entrepreneurial activity (Stam, 2015). Factors enabling entrepreneurial activity are present in social, cultural, and economic dimensions (Castaño et al., 2015). Stam (2015) proposes a set of ten interrelated EE-factors, called elements, that influence productive entrepreneurship. Examples of these elements encompass knowledge in local workforce, also named talent, (Nelson, 1981) and institutions which can enable or constrain entrepreneurial behaviour (Stam, 2012).

These entrepreneurial ecosystem elements can be mobile and may interact at all sorts of spatial levels (Bruns et al., 2017; Wurth et al., 2022). Knowledge has been proven to have spillovers across regions (Acs & Sanders, 2012; Moreno et al., 2005). Further, human capital can also move across regions through commuting and therefore also influence nearby EEs (Fraiberg, 2017; Schäfer & Henn, 2018). In contrast, formal institutions or infrastructure elements are regionally bound, and do not easily spill over.

The EE consists of networks of actors that operate under an institutional regime (Van Rijnsoever, 2020). This system operates at a regional scale, as entrepreneurs use local resources such as knowledge and financing (Malecki, 2018). However, research on EEs has also been undertaken on a national scale (Ács et al., 2014; Bruns et al., 2017); moreover, the networks of the ecosystem's actors are not restricted by this regional size and frequently span at the national or international level (Cortinovis & van Oort, 2019; Fischer et al., 2022). Hence, the boundaries of EEs cannot be set by political or administrative boundaries but span to where entrepreneurs draw their inputs to entrepreneurial output. However, currently EE-quality assessment is generally conducted on administrative-bounded regions (Schäfer, 2021).

Using the administrative-bounded regions, but accounting for the elements that may spillover from neighbouring regions gives a larger understanding of the entrepreneurial activity of regions. Thereby the overall insight on EE-quality would be enhanced (Schäfer & Henn, 2018). Discovering what resources flow freely into regions can also present large improvements on regional policy (Capello, 2009), as better decisions can be made when having insight on these resource spillovers.

This study seeks to address this gap by studying spillover of entrepreneurial ecosystem resources between neighbouring entrepreneurial ecosystems. Therefore, the proposed research question is:

What is the effect of entrepreneurial ecosystem resources of neighbouring regions on the entrepreneurial ecosystem performance of a focal region?

To address the research question, the EE-element spillovers between neighbouring EEs in 26 nations of the European Union (EU) and the United Kingdom (UK) has been analysed. Seven hypotheses were developed based on entrepreneurial ecosystem and resource mobility theory. A quantitative research method using spatially lagged variables in an ordinary least squares (OLS) model has been executed, which allowed to control for the spatial context. The innovative entrepreneurial output was modelled trough local and spatially lagged variables to confirm or deny the hypotheses.

This study enhances the understanding of the impact entrepreneurial resources from neighbouring regions may have on a focal region. From a scientific standpoint, spillover effects between EEs have never been quantitatively investigated, making this research an important addition to the current academic literature. On a societal level, the findings of this study are of relevance because they can help policymakers choose where to strategically deploy their resources to foster a more entrepreneurial and innovation-driven society.

2. Theory

To discover if certain elements of entrepreneurial ecosystems influence neighbouring regions, firstly the entrepreneurial ecosystems framework will be discussed. Second, resource mobility theory will be outlined, to understand how resources have an effect over geographic distances. A combination of these two will provide a theoretical base to this research.

2.1 Entrepreneurial Ecosystems

Isenberg (2011) proposes that the shortest path to starting a virtuous cycle of entrepreneurship is to create, enhance, cultivate, and evolve a geographically concentrated ecosystem dedicated to entrepreneurship and its success. If done right this EE enables entrepreneurship and value creation (Autio et al., 2014). Stam (2015, p. 1765) defines EEs as *"A set of interdependent actors and factors coordinated in such a way that they enable productive entrepreneurship"*. Productive entrepreneurship creates not only value for the entrepreneurs themselves but for society as a whole (Baumol, 1990). This is done by recognizing opportunities and taking risks, mobilising resources, and creating new business models that are adapted to the local environment (Sautet, 2013). This innovative behaviour of entrepreneurs is also known as innovative entrepreneurship (Szabo & Herman, 2012), as opposed to replicative entrepreneurs who launch businesses based on already existing ventures (Baumol, 2010). As such, innovative entrepreneurship is seen as the valuable output of an EE. Furthermore, this greater economic and social value can enable further entrepreneurship, thus a well-functioning EE gives rise to a self-reinforcing entrepreneurial cycle (Isenberg, 2011; Malecki, 2018).

System framework

As any ecosystem, there is a start, the EE starts as a small network of actors and evolves as entrepreneurial success attracts more financial resources, creates more skilled workforce, and forms new organizations (Spigel & Harrison, 2018). Mason and Brown (2013) discuss a turning point in EE development where new-ventures and spin-offs reach a point where it becomes a positive feedback loop. Brown and Mason (2017) provide a fitting model using the concepts of embryonic and scale-up ecosystems. These concepts describe development of EEs, whereas scale-up ecosystems are more advanced systems with a high level of start-ups and well-developed elements. This kind of ecosystem provides the resources for start-ups to grow into large ventures and enables complex connections and focus to expand outward beyond territorial boundaries (Brown & Mason, 2017). As a result, neighbouring regions might benefit from these highly developed ecosystems, also known as the borrowed size effect (Schrijvers et al., 2021).

As ecosystems can be at various phases of development, there are variations in amount of entrepreneurial activity across geographical spaces (Malecki, 2018; Mason & Brown, 2014). To explain entrepreneurial activity output of regions ten elements were combined to quantify regional entrepreneurial performance (Leendertse et al., 2022; Stam, 2015; Stam & van de Ven, 2021). These ten elements are: formal institutions, culture, networks, physical infrastructure, finance, leadership, talent, knowledge, demand, and intermediate services. EE quality has been measured with these ten elements on national (Ács et al., 2014; World Economic Forum, 2014) or regional scale (Leendertse et al., 2022; Schäfer, 2021; Stam, 2015; Stam & van de Ven, 2021). These studies however did not account for external resources, coming from other areas, influencing that certain area. Resources for EEs can be present on any spatiality (Wurth et al., 2022). Digitalization has enabled entrepreneurship on a global level (Moriset & Malecki, 2009), decreasing local resource dependence by increasing interconnectivity of organisations (Autio et al., 2018). Finally, as an EE evolves its spatial features may change (Schäfer, 2021), furthermore it can attract resources from adjacent regions or nations (Fischer et al., 2022). These perspectives pave way to look at how ecosystems affect nearby ecosystems. Theory on resource mobility expands on how EEs might be affected by neighbouring EEs.

2.2 Resource Mobility Theory

Externalities from market actions with effects on parties other than the parties involved are called spillovers (CFI Team, 2022; Hutchinson, 2017). These spillovers, if positive, provide a free resource to the receiver and are thus of great interest for policy interventions (Capello, 2009). Literature identifies multiple types of spatial spillovers, most popular being knowledge spillovers. Through diffusion, knowledge spillovers create value for organizations other than their origin (Fischer et al., 2006; Moreno et al., 2005). As a result, firms are motivated to be located close to these spillovers, as this significantly increases their growth (Audretsch & Lehmann, 2005) and entrepreneurial opportunities (Audretsch et al., 2006). Furthermore, knowledge is also able to spill over onto neighbouring regions and countries (Ertur & Koch, 2007; Moreno et al., 2005).

Another important type of spillover is the growth spillover, which refers to regional growth as a result of growth of a neighbouring region (Arora & Vamvakidis, 2005). Regional growth enhances local income, with a following higher demand for goods, more internal savings and better employment opportunities (Capello, 2009). Greater demand means more imports from surrounding regions. As EEs are seen to go through constant renewal, and no decline (Malecki, 2018), growth spillovers also seem relevant for EEs. López-Bazo et al. (2004) have shown that in EU regions, spillover effects resulting from growth are not negligible and should be considered when measuring region performance. Additionally, the related borrowed-size effect suggests that benefits of agglomeration in a city or region may be shared through networks and are important for understanding current dynamics of European urban regions (Meijers & Burger, 2017). As the borrowed-size-effect might empathize the positive effects between agglomeration economies and their neighbours, there also can be a negative effect due to competitiveness, called 'agglomeration shadows' (Meijers et al., 2015). Smaller regions might not profit of having a better scoring neighbour, but the better scoring region might use these smaller regions as additional resource pool. Burger et al. (2014) have shown this to be true for cultural amenities in North-West Europe, whereas the events are mainly drawn to the metropolitan areas. Concluding, growing regions, can create increased spillover resources, but also can act as a dominating region, 'overshadowing' neighbouring regions and absorbing their resources.

Looking at the evolution of EEs, it begins with a region developing some entrepreneurial activity. However, as the resource base develops, organizations might produce and attract human capital and entrepreneurs to that region, further accelerating growth (Mason & Brown, 2014). This is in line with how industry agglomeration happens following Marshall's theory, greatly improving economic progress within a region through; (1) reducing transport costs through proximity to suppliers or consumers, (2) labour market consolidation enabled by agglomeration, and (3) agglomeration encouraging intellectual interchange (Ellison et al., 2007). This could cause a form of resource-pull by growing ecosystems also highlighted by the concept of 'agglomeration shadows'. Recent research by Cavallo et al. (2021) states that innovative start-ups tend to locate close (within 30km) to industrial clusters, even though not having the same type of industry specialization.

In conclusion, resource mobility and spillover theories highlight potential benefits of geographical proximity to resources. These theories indicate that entrepreneurial activity could be fostered through beneficial spillovers or be attracted towards resources due to agglomeration advantages. Growth spillovers not only suggest potential benefits but also the disadvantages of being located near high-performing regions. This presents an opportunity to measure the potential cross-regional influences of resources, further exploring how EEs can impact one another.

2.3 Entrepreneurial Ecosystem Resource Mobility Framework

The Stam and van de Ven (2021) social system framework includes the EE-elements in multiple ontological layers: institutional arrangements, resource endowments and outputs. Institutional arrangements are the framework conditions that enable or limit socio-economic interaction (Stam, 2015). These are area-specific context elements that enable entrepreneurs to assess and access business possibilities (Audretsch & Belitski, 2017). While they are highly significant for an EE's internal workings since they are the enabling structure (O'Connor & Audretsch, 2022), they are considered immovable to other EEs. Therefore, institutional arrangements, the fixed structure to one's region, are deemed to not cause positive externalities. The resource endowments are the systemic conditions that enable entrepreneurial actions through providing certain resources (Stam, 2015). As the resource endowments are seen as the resources for entrepreneurial activities, their ability to cause positive externalities for neighbouring regions is tested trough several hypotheses. The output of the EE is innovative entrepreneurship. See figure 1 for the EE model. The self-reinforcing cycle of entrepreneurship is included with arrows showing that the output and outcome improve the EE-inputs.

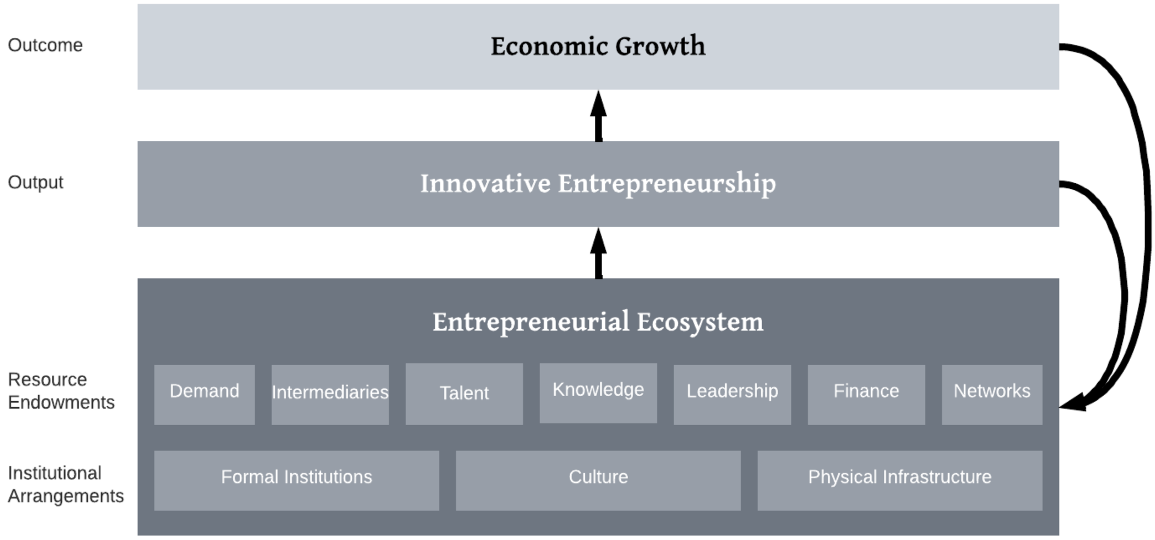

Fig 1. *Elements, output, and outcome of an entrepreneurial ecosystem (Adapted from Stam, 2015; Stam & Van de Ven, 2021; Leendertse et al., 2022).*

Output: Innovative entrepreneurship

Innovative entrepreneurship, formerly stated as productive entrepreneurship, is the main output that is relevant for this research. This kind of entrepreneurship has higher job creation and larger economic growth impact than other types of entrepreneurship (Stam & van de Ven, 2021). Innovative entrepreneurship is often captured trough prevalence of High-Growth Firms (HGFs) (OECD, 2011). A HGF is a firm younger than 10 years with over 10 employees that has realised an annualised revenue growth greater than 20% for a period of 3 years (EUROSTAT, 2007). In conclusion, start-ups with high potential tend to grow rapidly and become successful because of innovative entrepreneurship.

Hypotheses

In the next paragraphs, using theory of resource mobility effects & EEs, the seven resource endowments are argued on their ability to spill over geographical distances.

Demand spillovers

Demand is defined as the need of a population to purchase goods and services. For entrepreneurship to be effective, demand needs to be present. Furthermore, the greater the demand, the bigger the opportunities for entrepreneurship (Grilo & Thurik, 2004). It is of importance that the local population has the financial means to buy the goods and services (Leendertse et al., 2022). Neighbouring regions can have increased demand for a specific region's products thereby increasing local demand (North, 1955). Neighbouring demand for a region's products has extensively been linked to regional growth (Pike et al., 2016). Thus, in addition to internal demand, demand from neighbouring regions appears to be a driver of entrepreneurial activity in regions.

H1: *The level of Demand in neighbouring regions has a significant positive effect on the entrepreneurial ecosystem outputs of a focal region.*

Talent spillovers

Talent is defined as human capital in the form of a set of skilled workers, who entail high levels of creativity and social diversity[2] (Lee et al., 2004). A highly skilled workforce enhances survival and competitiveness of new ventures and brings large economic value in the public and private sector (Haveman & Wolfe, 2002; Qian et al., 2013). Cities and regions have challenges in attracting and retaining valuable human capital. For example, in Bangalore, a thriving EE, talent is attracted from five surrounding states, negatively impacting those ecosystems (Goswami et al., 2018). Talent is seen as a mobile source as it is made up of individuals who have their demands for a way of living (Qian, 2018). Furthermore, research by Backman and Karlsson (2017) has shown that entrepreneurs who are used to commuting rather start a business at the location of their strongest business network than their place of residence. Better interconnectivity leads to more individuals wanting to commute for economic reasons (Blum et al., 1997), which leads to the conclusion that talent may spillover between regions.

H2: *The level of Talent in neighbouring regions has a significant positive effect on the entrepreneurial ecosystem outputs of a focal region.*

Intermediary spillovers

Intermediaries are specialised firms that provide a wide range of services, such as structuring established or emerging businesses, navigating complex tax and legal issues, sourcing technology solutions, providing investment services, and accessing strategic advice (Yan & Li, 2010). They can also help to improve the networking capabilities of entrepreneurs and their businesses through incubation services, giving them access to non-internally present capabilities (Spigel, 2017). Moreover, supporting newly established companies can have a positive impact on the EE (van Rijnsoever, 2020). Mas-Verdu et al. (2010) suggest that intermediaries can provide a link between firms and resources outside of their local network, which Bramwell et al. (2019) have demonstrated to be essential for connective functions within and between different ecosystems in Canada. Furthermore, intermediaries consist of individuals/organisations, just like Talent, which can commute to other regions for services. This leads to the following hypothesis.

H3: *The level of Intermediaries in neighbouring regions have a significant positive effect on the entrepreneurial ecosystem outputs of a focal region.*

Knowledge spillovers

Knowledge is defined as novel knowledge through study, research and experiences, which can be created by public or private organisations (Qian et al., 2013). Novel knowledge, created by investments in R&D, has proven to increase start-up occurrence in regions (Audretsch et al., 2006). Knowledge spills over to other actors in the region, which can increase their capabilities and enable entrepreneurial activities (Acs et al., 2013; Agarwal et al., 2010). Knowledge is recognized as a mobile resource, as it transfers over regional and even national boundaries (Coe, 1993; Ertur & Koch, 2007; Moreno et al., 2005). Knowledge may also spillover through social networks, even further extending its geographical capabilities (Autant-Bernard et al., 2007). Knowledge seems to spread over distances and through networks, making it a mobile resource, which leads to the following hypothesis.

H4*: The level of Knowledge in neighbouring regions has a significant positive effect on the entrepreneurial ecosystem outputs of a focal region.*

Leadership spillovers

Leadership is defined as the process of change where an individual's ethics are integrated into the norms and beliefs of social groups, thereby motivating transformative change (Hunt, 2004). Leadership is essential for ensuring a healthy ecosystem, as it provides a clear vision and direction for increasing efficiency and productivity (Normann, 2013). The commitment of these regional leaders also might

[2] Workforce which is socially diverse has more creativity and is more open to new ideas.

reflect the underlying norms dominant in a region (Feldman, 2014; Leendertse et al., 2022). Leaders who have experience in entrepreneurship often have business experience and an extensive network of connections, which can position them well to take advantage of entrepreneurial opportunities in new locations (Frederiksen et al., 2016). Entrepreneurs with strong leadership skills are more likely to start successful ventures when moving abroad (Mukesh & Thomas, 2016). Overall, this experience and access to resources through a social network can give leaders an advantage when it comes to starting and growing businesses in unfamiliar environments. Just like Talent, this resource may spillover through individuals who undertake entrepreneurial activities elsewhere than their residence.

H5: *The level of Leadership in neighbouring regions has a significant positive effect on the entrepreneurial ecosystem outputs of a focal region.*

Finance spillovers

Finance is defined as financial capital, which is needed for start-ups to establish an office, hire employees, and expand business (Bartlett & Economy, 2002). Access to finance has been identified as an important factor in the EE, as it supports survival and growth of new ventures (Stam & van de Ven, 2021). Furthermore, financial capital may enable entrepreneurs to undertake more ambitious strategies and meet demands imposed by firm growth (Cooper et al., 1994). Private equity investing by venture capital or other forms of investors occurs across borders as for 2019 in the EU €2.8 billion of the €9.5 billion venture capital was invested across country borders (Invest Europe, 2019). Chen et al. (2010) found that venture capital businesses in regions with a high concentration of successful investments perform better. Non-local investments additional to local investments also boost this performance. These venture capital firms capitalize on prospects outside their focal region. Overall, it appears that financial capital is a resource that flows both locally and across borders.

H6: *The level of Finance in neighbouring regions has a significant positive effect on the entrepreneurial ecosystem outputs of a focal region.*

Network spillovers

A social network is defined as a set of connected individuals or organisations, often based on the same interests, goals and/or values (Granovetter, 1983). The presence of social networks will connect entrepreneurs with other relevant actors, to allow free flow of knowledge, skills and other resources (Spigel, 2017). Granovetter (1983) argues that it is very important to have bridging ties, that span different networks, for valuable new inputs for own business goals and objects. These bridging ties spreading for example knowledge can span to 250km (in the EU), and cross administrative regional borders (Fischer et al., 2022). Furthermore, network linkages are found to be directional whereas less technologically advanced (firms in) regions learn from R&D investments in more advanced regions (Cortinovis & van Oort, 2019). Extensive regional networks can cross or spill over into other regions, expanding access to certain resources, concluding that networks are a mobile resource.

H7: *The level of Networks in neighbouring regions has a significant positive effect on the entrepreneurial ecosystem outputs of a focal region.*

3. Methods

This section starts with a discussion of the level of analysis and data sources. This is followed by an explanation of the research's variables and how they are measured using various indicators. This chapter continues with a delineation of the spatial methods and models utilised for analysis, ending with some quality requirements.

3.1 Level of analysis & data sources

Europe is regarded as a favourable testing ground for EE analysis as there is a wide variety of entrepreneurial activity between regions and good data availability (Leendertse et al., 2022). For studying EEs, a local scale has been deemed most appropriate (Malecki, 2018), being it city or (small) province based. A conventional approach for quantitative research is taking administrative units due to data availability (Fischer et al., 2022).

For the EU the NUTS[3] spatial area units form clear administrative boundaries, ranging from NUTS 3, small regions containing up to 800.000 inhabitants, to NUTS 1 being major economic regions ranging 3 to 7 million inhabitants (Ortega-Argilés et al., 2014). NUTS 3 is argued to provide an accurate distinction in regions, as entrepreneurship is deemed to be a local phenomenon (Autio et al., 2014; Bosma & Sternberg, 2014). However, in spatial spillover research NUTS 1 and 2 scale has often been used for measuring spillover effects in Europe (Baumont et al., 2001; Fingleton & López-Bazo, 2006). Quantitative analysis on EE performance is mainly based on NUTS 2 scale (Bruns et al., 2017; Leendertse et al., 2022; Stam & van de Ven, 2021). Therefore, this research used NUTS 2 scale as the unit of analysis. This analysis has focus on 260 NUTS 2 EU and UK regions from 26 nations, as these NUTS 2 regions all contain at least one neighbour. Therefore, isolated NUTS 2 regions such as islands or overseas regions from EU nations were excluded from this research.

The methodological steps regarding the data sources and indicators are reused from Leendertse et al. (2022). This data was mainly extracted from public EU instances such as EUROSTAT, OECD and CORDIS, with complementary data from private organisations such as Crunchbase and Invest Europe.

3.2 Operationalisation of variables

The ten elements are constructs, or functions that play a role in an EE (Stam, 2015). Although there is no one-size-fits-all method for quantifying these elements, indicators can be utilised to gather enough data to gain an overall understanding. Leendertse et al. (2022) have developed a variety of indicators for measuring the ten elements, which are reused in this research. Table 1 provides an overview of all variables used in this research.

Dependent variable: Innovative entrepreneurship

As stated in the theory, the main output of regional EEs is innovative entrepreneurship. Not all new firms are a result of innovative entrepreneurship, so a measure different than simply the total number of new firms, also called “gross entrepreneurship”, is required. Nicotra et al. (2018) delineate multiple forms of indicators for measuring productive entrepreneurial output. Firstly, assumption-based indicators are based on factors that could indicate a new firm is putting out productive entrepreneurship. These include being an innovation-based or VC-backed start-up. Secondly, performance-based indicators could be used, which are focussed on economic growth and job creation within start-ups. HGF occurrence is commonly used as a performance-based indicator.

The Crunchbase database of innovative companies and start-ups is frequently used by economic and managerial research (Dalle et al., 2017). Innovation-based, VC-backed start-ups make up this database, seemingly the assumption-based indicators. Start-up databases, such as Crunchbase and Dealroom have

[3] The Nomenclature of territorial units for statistics (NUTS) is a hierarchical system for dividing up economic territory of the EU and UK, whereas NUTS 2 are basic regions for the application of regional policies (EUROSTAT, n.d.).

been proven to have a positive correlation with HGF occurrence (El-Dardiry & Vogt, 2022). Therefore, this study used Crunchbase start-ups per capita in a period from 2017-2021 to measure innovative entrepreneurship, resulting in a total of 46.661 innovative firms.

Independent variables

As there are seven elements which are deemed spillable over distance in this research, these seven have been used as independent variables. The extensive description of indicators for measuring these variables can be found in Appendix A. For two elements, Knowledge and Networks, the indicators have been changed[4] compared to Leendertse et al. (2022). Their adaptations are described below.

Knowledge

Creation of novel knowledge has been proven as an important resource for entrepreneurship (Qian et al., 2013). For measuring knowledge in regions, accepted patent applications per capita for the period from 2014-2016 has been taken. As more patents are accepted in a region, more knowledge is produced, which can pave way for business opportunities. The data has been retrieved from the EPO REGPAT database where all application origins can be linked to NUTS-2 regions (OECD, 2022).

Networks

Social networks are recognized to let entrepreneurs share knowledge, creativities, and other resources (Spigel, 2017). In entrepreneurship connections that (young) firms undertake are seen as relevant networks. Following Leendertse et al. (2022) regional networks are measured through "*the number of Small and Medium Enterprises (SMEs) that undertake cooperation activities in the form of projects as the total number of SMEs in a region*". However, as an addition the normalized values for 2016 and 2017 have been taken to give a better overview over time. This data was retrieved from the RIS database.

Control Variables

Internal Structure

Outside of the seven resource elements other factors influencing innovative entrepreneurship within a region. To ensure that these last elements are considered, they are included as control variables within the model. A composite factor named Internal Structure has been created which compromises the elements Formal Institutions, Culture and Physical Infrastructure[5]. Internal structure accounts for the 'institutional arrangements' of a region, which in theory do not influence neighbouring regions, therefore controlling for innovative entrepreneurship within a region.

Capital

In line with Leendertse et al.'s (2022) findings, which highlight the significant positive effect of being a capital region on innovative entrepreneurship output, this study also incorporated Capital as a dummy variable. The integration of this variable helps pointing out the advantage of being a nation's capital and allows for more understanding how this affects the independent variables. By including this variable there is a higher control for specific regional characteristics.

EE-index

For measuring the total performance of an EE, Leendertse et al. (2022) developed a method using quantification indicators for the ten EE-elements on 273 regions in 28 EU countries. This method resulted in an EE-index score for each NUTS 2 region analysed. The score is used in this research to verify that EE performance is linked to innovative entrepreneurship. Therefore, it is a control factor in the overall research.

---

[4] Both original and new variables have been tested. The new variables show better consistency and have an improved impact on innovative entrepreneurship. See Appendix B for the original indicator models.

[5] See appendix A for elaboration on these structural elements.

Table 1: Summary of research variables

Variable	Indicator(s)	Measurement and description	Source	Geo-level
Dependent variable				
D1: Innovative entrepreneurship	Innovative start-ups	Nº of new innovative firms' per capita period of 2017-2021.	Crunchbase	NUTS-2
Independent variables				
H1: Demand	Disposable income	Disposable income per capita.	EUROSTAT	NUTS 2
	Market size in GRP	Index GRP PPS (EU population-weighted average = 100)	EUROSTAT	NUTS 2
	Market size in population	Index population (EU average = 100)	EUROSTAT	NUTS 2
H2: Talent	Tertiary education	Percentage of total population	EUROSTAT	NUTS 2
	Lifelong learning	Percentage of working population participating in education and training	EUROSTAT	NUTS 2
	Business and entrepreneurship education	The extent to which training in the creation or management of SMEs is integrated into the educational and training system. Scale: 1-5	GEM	Country
	E-skills	Percentage of individuals with high levels of e-skills	EUROSTAT	Country
H3: Intermediates	Knowledge-intensive marketing services	Percentage of employment in KIMS.	EUROSTAT	NUTS 2
	Incubators	Number of incubators per capita	UU-database	NUTS 2
H4: Knowledge	Patents	Accepted patent applications per capita period of 2014-2016.	EPO (REGPAT)	NUTS 2
H5: Leadership	Project leaders	Number of innovation project leaders of Horizon 2020 projects per capita.	CORDIS	NUTS 2
H6: Finance	VC-investments	Total VC invested by private equity per capita.	Invest Europe	NUTS 2
	Credit constrained SMEs	Percentage of SMEs that is credit constrained because of loan rejection or received less, or were discouraged to apply because of expenses or chance of decline	Investment Survey European Investment Bank	Country
H7: Networks	Innovative SME collaborations	Average percentage of SMEs in SME business population collaboration to the total in 2016-2017.	RIS & EIS	NUTS 2
Control variables				
CV1: Internal Structure	Formal Institutions	Quality of Gov Index scores Ease of Business index scores	QoG Index & EDB Index	Country, NUTS 1 & NUTS 2
	Culture	Entrepreneurial motivation & entrepreneurial acceptance scores. Trust & innovation motives.	GEM & European Social Survey	Country, NUTS 1 & NUTS 2
	Physical Infrastructure	Accessibility by road, accessibility by rail and flight accessibility. Household access to internet.	RCI & EUROSTAT	NUTS 2
CV2: Capital (dummy)	Capital status	Being a region containing a nation's capital	Own data	NUTS 2
CV3: EE-index	EE-index additive scores	Score based on quantification of the ten EE-elements.	Leendertse et al. (2022)	NUTS 2

3.3 Data analysis

First, all gathered data was combined in one database. Because of varying data types, such as percentages and numerical values, all indicator values were standardized to make them comparable (Nardo et al., 2005). As one of the regression models required no-negative values, the summed lagged effect, all values have been made positive by adding four to all variables. For consistency in the results these transformations led to the final dataset utilized for the research.

The descriptive statistics of the relevant variables in this research are presented in appendix C. The standardization and transformation of the data causes the consistent value of 4 for the means and 1 for the standard deviations. Internal Structure has a different mean and standard deviation due to a principal component analysis (PCA)[6], which combined three variables to one composite variable. Capital as a dummy variable varies between the value 0 and 1, due to 29 regions being capital, most regions have a value of zero in this variable. The EEI is a continuous variable ranging from 1.3 to 35. The maximum lagged variables are roughly the same as the local variables, however, the mean is 0.4 to 0.8 higher in all cases.

The correlation matrix, present in appendix C, presents the correlation coefficients of all variables. All correlations between the internal EE-elements are significant and thus accentuating the systemic nature of EEs (Stam, 2017). Most maximum lagged variables show positive correlations with the dependent variable and internal independent variables. All lagged variables show significant positive correlations with each other, indicating again consistency in the EE-elements. The correlations suggest that Intermediate, Leadership, and Internal Structure have a significant strong influence on Innovative Entrepreneurship. However, it's important to remember that correlation does not imply causation, and further analysis would be needed to establish causal relationships.

Outliers are mainly present in the variables Innovative Entrepreneurship, Intermediate, Knowledge and Leadership. The extreme outliers (over 5 standard deviations) include regions such as UKI3-4 (Inner London - East & West) due to excessively high Intermediate and Innovative Entrepreneurship, DK01 (Copenhagen) for elevated Leadership scores, and DE21 (Oberbayern) for unique Knowledge. Removing these outliers (see appendix D) led to Intermediate effects not being significant anymore, suggesting that the original significance of the Intermediate variable might have been driven by the extreme value in UKI3-4. All other variables were consistent with the results. As there is no theoretical or methodological argument to exclude these outliers, they are included in the main results.

3.4 Regression Analysis

Regression model

The hypotheses are tested through a series of regression models. First, the local effects of the elements are validated through an OLS model. These models are then expanded to spatial models with spatially lagged independent variables to account for spillover effects. Finally, multiple variations of spatially lagged independent variables were run to confirm the results and discover additional explanations.

The dependent variable (i.e. number of innovative entrepreneurship firms) is an integral variable which can only take non-negative values. Normally this count variable leads to using either Poisson models or negative binomial models (Coxe et al., 2009). However, since the dependent variable is standardized towards a normal distribution an Ordinary Least Squares (OLS) is in place. Below is an example of an OLS regression.

Example OLS regression:

$$y_i = \alpha + \beta \chi_i + \varepsilon_i$$

[6] PCA identifies directions (principal components) in which the data varies the most. The first principal component accounts for the largest possible variance in the data. In this case the created composite explains 77% of the total variance created by the three original elements.

Where y_i is the continuous dependent variable as a function of i^{th} observation and χ_i is a matrix of independent variables, β is a vector of the regression parameters, α is the constant of the regression and ε_i is the error term (Casella & Berger, 2002).

In a conventional OLS one assumption is that the dependent variable observations are independent of each other, however as we argue regions influence each other, this assumption is broken (LeSage & Pace, 2009). To see if dependent variable observations are independent of each other, the residuals must have a random distribution. A spatial autocorrelation test, called Moran's I is run which proved that the OLS models have spatial autocorrelation, see table 2. The positive values ranging from 0.2 to 0.4 are considered moderate positive autocorrelation. There is some form of clustering, which shows that regions with similar values are somewhat near to each other (Dubé & Legros, 2014). Spatial lagged variables are applied to account for this spatial autocorrelation to get more insight into how the regional effects are correlated (Anselin & Bera, 1998).

Table 2: Moran I test results

Model Residuals	Moran's I statistic	p-value
Demand OLS model	0.2118	4.724e-07
Talent OLS model	0.2019	1.439e-06
Intermediate OLS model	0.3899	< 2.2e-16
Knowledge OLS model	0.2554	1.862e-09
Leadership OLS model	0.2017	1.425e-06
Finance OLS model	0.2229	1.247e-07
Networks OLS model	0.1999	1.815e-06

It is essential to have a clear understanding of which other regions a certain region can interact with before the establishment of any spatial linkages. A spatial weight matrix is used to specify this, expressing for each observation which places are its neighbours (Anselin & Bera, 1998). For this research first-order contiguity is used, this entails that regions must be bordering and are direct neighbours, thus, to measure local spillovers (Vega & Elhorst, 2015). This weight matrix is used to create various lagged spillover effects. Appendix E contains a summary of the spatial weight matrix.

The spatial lag effects were created by using the 'spdep' package in R (Bivand et al., 2013). The shapefile for the NUTS 2 EU regions was retrieved from the GISCO database (*NUTS - GISCO - Eurostat*, n.d.). Inner-Londen East and West[7] were combined using ArcGIS, which resulted in the final 259 regions used in the research. A neighbour network was created using the 'spdep' package. Manual interventions were required to add the close connections between Hovedstaden (DK01) and Sydsverige (SE22) and between Sjælland (DK02) and Syddanmark (DK03), facilitated by bridges, which the neighbour function did not automatically recognize. Additional linkages have also been tested, based on travel distance; this however did not change the outcomes (see appendix F). The resulting neighbour network is shown by figure 2. The neighbour network matrix and the variable dataset enables creation of several types of spatial lag, crucial for our analyses.

[7] Due to the existing dataset, which combined UKI3 and UKI4, they also had to be combined within the shapefile.

Fig 2. *Neighbour network of European NUTS 2 regions.*

Spillovers usually occur when there is an agglomeration of a certain resource in a region, such as knowledge or other public goods (Capello, 2009). Therefore, the largest nearby quantity, the maximum value, in surrounding regions is the focus in the spatial analysis. The maximum value of the neighbouring regions is taken to see how the 'resource-richest' neighbour might affect the focal region. Hereby, the effect of having a well-performing neighbour becomes visible, thereby enabling an answer to the research question. Other measurements of spatial lag were also applied in this research to validate the results and seek further explanations. The average lag is one of the main ways spatial spillovers are researched (LeSage & Pace, 2009), this lag takes the average of surrounding regions, mainly enabling a general view of spillovers. Furthermore, the sum of values is taken to see the aggregate value of neighbouring region elements that might spillover. The sum of neighbouring regions may be very large due to some regions containing up to eleven neighbours[8]. Therefore, for methodological reasons a log transformation is applied on the summed variables to create a more even distribution which is an improved input for the regression models. The final measurement for spatial lag is the minimum of neighbouring regions. The goal of this spatial lag was to check for reverse results and see if having lower scoring neighbours is potentially negative for local innovative entrepreneurship.

To account for the spatial context in regression models, the spatially lagged variables were included into the set of local explanatory variables (Florax & Folmer, 1992). Adding spatially lagged variables creates a spatial regression, which allows to encompass neighbouring effects (LeSage & Pace, 2009), therefore creating a spatial lag of X model (SLX) (Vega & Elhorst, 2015). For each variable, element, that contains spillover potential spatially lagged variables were created. Including these spatially lagged variables provides understanding on the impact of neighbouring regions independent variables on the dependent variable of a focal region. A sperate model is created for every element, accounting for the local effects and the potential spillover effects. An example of a spatial model is shown below.

[8] An additional CV accounting for number of neighbours was introduced, this led to large model performance issues, so this CV was discarded.

Example OLS regression accounting for spatially related variables:

$$y_i = \alpha + \beta\chi_i + \theta W\chi_1 + + \varepsilon_i$$

The added θ is a scalar parameter that captures the influential strength of the neighbour's independent variables and $W\chi_1$ is the lagged independent variable value of the neighbours. This captures a one-way effect from the neighbour's independent variable to the focal region's dependent variable.

To assess total EE spillovers, we utilized the EE-index (EEI) formulated by Leendertse et al. (2022). The EEI assisted into uncovering the effect of the EE on innovative entrepreneurship and its potential effect on neighbouring regions. This step provided an overview of potential system spillovers and indicated that deeper analysis on the individual variables was necessary (see appendix G). Following this preliminary analyses, each variable was analysed through OLS and spatial regression models. The robustness of the results was affirmed through various types of spatial lag models. Finally, a deeper dive into spatial spillovers was taken by examining the specific interactions between local and spatial lag effects through interaction effect models. To investigate this, an interaction term is created between the local element and spatially lagged element and included in the regression model. Furthermore, a 'better' neighbour dummy is tested to uncover if better neighbours, not based on size of values, has an influence on focal EE performance. This uncovered some interplay that was not visible from the spatial lag models in the results section, thus offering some deeper understanding in the dynamics of the spatial spillovers.

In this study, each model was tested for quality using performance indicators. The Breusch-Pagan test (BP-test) was conducted to see if the variance of residuals was constant across the models. To address the high correlation of the variables in this research, each model is checked for multicollinearity using a Variance Inflation Factor test (VIF-test). Furthermore, goodness of fit was inspected through the adjusted R-squared values. Ensuring validity of the models was a critical aspect of the analyses, as this shows results were robust. This robustness led to more credibility of our findings and provides valuable insights into the relationships between the independent variables and the dependent variable. The entirety of the analyses, including modelling and testing, was executed using the statistical programming tool R[9] (R Core Team, 2013).

[9] The R code can be provided on request and is available on https://github.com/Boostveen/thesis.

4. Results

This section starts with descriptive statistics of innovative entrepreneurship in NUTS-2 regions in Europe. The second part contains the local OLS models. The third part focusses on the different elements and their spillover effects, and how these may influence innovative entrepreneurship in neighbouring regions. The fourth part is dedicated to the robustness of the results. The final part dives deeper into additional dynamics of the spillovers.

4.1 Descriptive results of dependent variable

In appendix H, the regions with the highest innovative entrepreneurial output are shown. The highest achieving regions are Inner-London East & West (UKI3-4), North Holland (NL32), Estonia (EE00), Flevoland (NL23). Interestingly it is visible that the best performing region of the dataset Inner-London East & West (UKI3-4) scores well above the mean, with all values in the top quartile of the overall dataset. Furthermore, it is visible that most regions in the top ten have above average scores on most variables accentuating that all elements are important for good performance of an EE. Overall, the Netherlands, the UK, Ireland, and Scandinavia have a well distributed high number of innovative firms per capita across their nations. Figure 3 illustrates this distribution, with a detailed focus on the Inner-London NUTS 2 area.

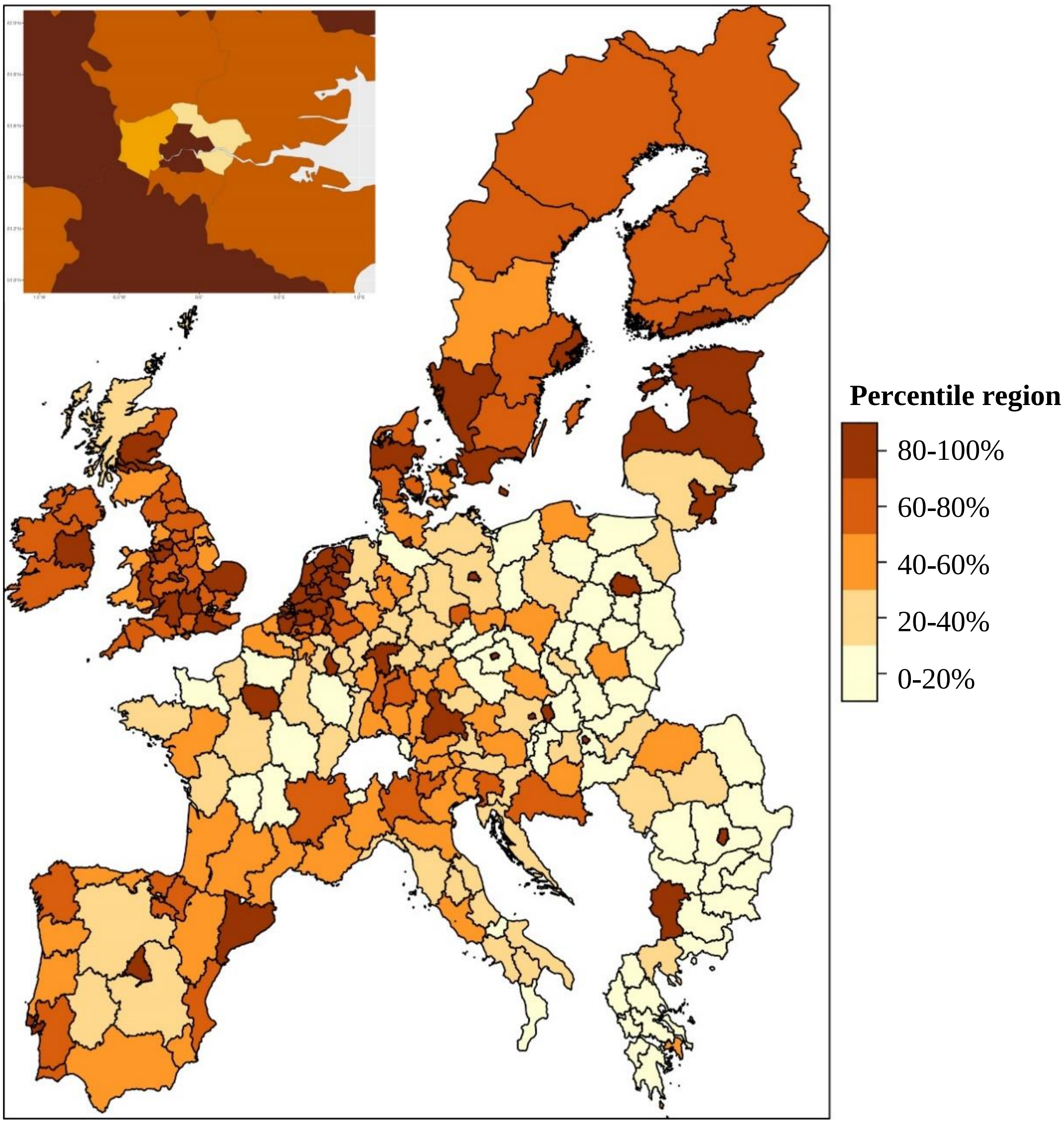

Fig 3. *Innovative Entrepreneurial output per region including zoom on the Inner-London area.*

4.2 Regression models

The local OLS models

Table 3 presents the results of the OLS models. The control model has an adjusted R squared of 0.368 indicating moderate variance explained. The following seven models are independent and each checks a different independent variable, all but Demand and Networks indicate model fit improvement. As for other model performance indicators, tests for multicollinearity and heteroskedasticity were performed. The VIF-tests indicated that there was no multicollinearity present, as all VIF scores were below the threshold of 5, with the highest VIF score being 2.9 for Talent. The studentized BP-test came back just significant for Demand with p = 0.04 and p = 0.003 for Intermediate, indicating that there is heteroscedasticity in this model. The other five models tested non-significant.

Demand and Networks have insignificant effects on the dependent variable and add no explanatory value to the control model. The remaining five elements all have a significant positive effect on Innovative Entrepreneurship.

Table 3: The OLS models

	Dependent variable: Innovative Entrepreneurship							
	Independent variables							
	Control model	Demand	Talent	Intermediate	Knowledge	Leadership	Finance	Networks
Internal Structure	2.079***	2.025***	1.438***	1.229***	1.820***	1.510***	1.637***	1.977***
	(0.169)	(0.214)	(0.284)	(0.138)	(0.188)	(0.150)	(0.275)	(0.221)
Local independent variable		0.026	0.232***	0.589***	0.163***	0.474***	0.164**	0.046
		(0.062)	(0.083)	(0.040)	(0.055)	(0.044)	(0.080)	(0.065)
Constant	1.228***	1.196***	1.156***	0.004	0.921***	0.089	1.163***	1.178***
	(0.231)	(0.244)	(0.229)	(0.191)	(0.250)	(0.219)	(0.232)	(0.241)
Observations	259	259	259	259	259	259	259	259
Adjusted R^2	0.368	0.366	0.384	0.653	0.386	0.564	0.375	0.366
Residual Std. Error	0.795 (df = 257)	0.797 (df = 256)	0.785 (df = 256)	0.589 (df = 256)	0.783 (df = 256)	0.660 (df = 256)	0.790 (df = 256)	0.796 (df = 256)
F Statistic	150.958*** (df = 1; 257)	75.321*** (df = 2; 256)	81.326*** (df = 2; 256)	243.462*** (df = 2; 256)	82.143*** (df = 2; 256)	167.866*** (df = 2; 256)	78.477*** (df = 2; 256)	75.593*** (df = 2; 256)
Note:								*p<0.1; **p<0.05; ***p<0.01

The spatial OLS models & hypotheses analysis

Building upon the OLS models, the following spatial models are shown in table 4. The adjusted R squared values of the seven spatial lag models indicate improvement compared to the control model. Leadership is the only variable that does not show improvement in model fit compared to the Leadership OLS model. The spatial models demonstrate statistical robustness with the highest VIF score noted at 4.6 on local Talent. An analysis of heteroskedasticity revealed that solely the Intermediate variable displayed significant heteroskedasticity. This implies that for all other models that the variability in the error terms are consistent. This contributes to the reliability of the coefficients and strengthens the validity of these models. The heteroscedasticity is cause by one extreme outlier[10], and not deemed to influence the validity of the results.

All local independent variable effects are significant and positive. The lagged Leadership effect doesn't show significance indicating it does not affect Innovative Entrepreneurship in a neighbouring region. All other lagged effects are significant and negative. These negative effects suggest that an increase in the highest independent variable from neighbouring regions has a negative effect on the focal EE output.

[10] See appendix D: Removal outlier models.

Table 4: Max lagged spatial models

	Dependent variable: Innovative Entrepreneurship							
	Independent variables							
	Control model	Demand	Talent	Intermediate	Knowledge	Leadership	Finance	Networks
Internal Structure	2.079***	2.118***	1.569***	1.458***	2.063***	1.544***	1.939***	2.010***
	(0.169)	(0.199)	(0.283)	(0.143)	(0.192)	(0.161)	(0.268)	(0.220)
Local independent variable		0.406***	0.423***	0.601***	0.203***	0.475***	0.393***	0.191**
		(0.083)	(0.104)	(0.039)	(0.054)	(0.044)	(0.088)	(0.094)
Max lagged variable		-0.548***	-0.279***	-0.136***	-0.136***	-0.020	-0.425***	-0.200**
		(0.086)	(0.093)	(0.030)	(0.033)	(0.035)	(0.082)	(0.096)
Constant	1.228***	2.025***	1.436***	0.277	1.070***	0.139	1.730***	1.442***
	(0.231)	(0.261)	(0.244)	(0.193)	(0.245)	(0.236)	(0.246)	(0.271)
Observations	259	259	259	259	259	259	259	259
Adjusted R^2	0.368	0.451	0.403	0.677	0.422	0.563	0.433	0.375
Residual Std. Error	0.795 (df = 257)	0.741 (df = 255)	0.773 (df = 255)	0.568 (df = 255)	0.760 (df = 255)	0.661 (df = 255)	0.753 (df = 255)	0.791 (df = 255)
F Statistic	150.958*** (df = 1; 257)	71.741*** (df = 3; 255)	58.978*** (df = 3; 255)	181.475*** (df = 3; 255)	63.711*** (df = 3; 255)	111.730*** (df = 3; 255)	66.688*** (df = 3; 255)	52.519*** (df = 3; 255)
Note:								*p<0.1; **p<0.05; ***p<0.01

The analysis of the seven hypotheses draws a remarkable picture of the entrepreneurial ecosystem and the effect neighbours have on a focal region. The seven hypotheses all stated that EE-elements exert a positive effect on neighbouring regions. Hypothesis 1 stated a positive impact of neighbouring regions Demand on the local entrepreneurial output. Instead, the results indicate that higher Demand in neighbouring regions has a negative effect on local entrepreneurial ecosystem outputs. Hence, not only is H1 rejected, but a contrasting effect is found. For five other elements, namely Talent, Intermediate, Knowledge, Finance, and Networks, the same pattern is discovered. Consequently, this causes rejection of Hypotheses 2, 3, 4, 6 and 7. This is in-line with the ‘agglomeration shadow’ concept, whereas being near a well-performing economy may see local resources absorbed by a stronger economy, and therefore negatively impacting local innovative entrepreneurship.

When it comes to Leadership, represented in Hypothesis 5, local Leadership has a strong, positive effect. However, the data provides no evidence of an effect from neighbouring regions, leading to the dismissal of H5. Initially, it was argued that Leadership, just like Talent, would be mobile, and thus influencing surrounding regions. However, this effect is not confirmed as no significance is discovered.

4.3 Robustness Results

The results are based on the highest neighbouring element effect; however, alternative methods of evaluating neighbouring region element spillovers exist. In addition, it is important to validate the robustness of the results. This validation involves trying out alternative models and performing relevant data transformations throughout the research to reaffirm the reliability and consistency of the results.

Average, Summed, and Minimum lagged models

Starting with the average lagged spatial models presented in appendix I. Nearly all models confirm the negative spillover effects. Only Networks shows no local or average lagged effect, possibly due to multicollinearity with the local Network variable and significant correlation with Internal Structure[11].

[11] See correlation matrix in appendix C.

Other effects were in line with the results. Shifting to the summed lagged spatial models, also in appendix I, all models demonstrate negative spillover effects. Interestingly, Leadership was also discovered to have a significant, negative effect reassuring that H5 is not correct, but also pointing out that a high level of leadership in the surroundings has a negative effect on innovative entrepreneurship in the focal region. Lastly, the minimum lagged models explored if low-scoring neighbours influence EE output performance positively. However, all models show non-significant lagged effects, suggesting minimal impact from low-scoring neighbours on the focal EE.

Capital CV model

As a secondary robustness check, an additional control variable, "Capital," was incorporated into the models to account for possible effects that a region's capital status might have on the output of Innovative Entrepreneurship (see appendix J). Across all models, the Capital variable demonstrated a positive and significant effect, which aligns with the findings of Leendertse et al. (2022) that capital status positively impacts innovative entrepreneurship output. The inclusion of the Capital control variable resulted in the lagged max Networks and Talent no longer displaying significant effects, suggesting a potential mitigating influence by the Capital variable, indicating lower robustness of the findings in these two elements. Other elements maintained consistent with the results presented in Section 4.3.

Exclusion of single-neighbour regions

In the third robustness check, regions with only a single neighbour were excluded under the presumption that these regions may have limited spillover potential due to their limited neighbourhood. This exclusion led to the removal of 15 regions from the analysis. Consequentially, the lagged effects for Talent and Networks lost their significance, and Networks also lost the locally significant effect. The other variables are consistent with the results (see appendix K).

4.4 Additional analyses

To provide a deeper understanding of the interplay between spatial spillover effects and innovative entrepreneurship further analysis is provided by looking into interaction and 'better' neighbour dummy effects.

Interaction effect analysis

An exploration of interaction effects has been undertaken to gain deeper understanding into how a region's element value interacts with the maximum element value of its neighbouring regions. The presence of significant interaction terms would imply that the impact of a neighbour's element value is dependent upon the local level of that specific element. You can find the detailed models of these interaction effects in Appendix L. Two significant interaction effects are identified. The max lagged Intermediate has a positive effect on local EE output, indicating the first positive spillover effect in this research. However, the interaction effect suggests that if a region's own Intermediate matches the high score of the max lagged Intermediate, it negatively impacts the local EE output. This implies the opposite for weaker performing regions. Regions that score lower on the Intermediate variable profit from being proximate to a high scoring region. A light significant interaction effect, with p-value of <0.1, is discovered in the Leadership model. This interaction suggests, just like with Intermediate, that if a region scores high itself and matches their neighbours score this negatively affects the Innovative Entrepreneurship output. The other five interaction effect models show no significant effects.

Better neighbour dummy

To underscore our observation that a neighbouring region with higher scores negatively impact a focal region's innovative entrepreneurship, we introduced a dummy variable for each element, which indicates whether neighbouring regions outscore the focal region. Detailed results of this analysis are provided in Appendix M. Notably, every effect identified was both significant and negative, reaffirming our initial findings. This data confirms the theory that having a higher-scoring neighbour can indeed negatively impact a region's innovative entrepreneurship output.

5. Conclusion

This thesis set out to find deeper explanations of variations in regional entrepreneurial activity. Existing literature mainly focusses on local internal resources, however, following Tobler's theory (1970), interregional influences could also be an additional factor for understanding regional entrepreneurship. For this study the concept of Entrepreneurial Ecosystems was utilized and acknowledged as a solid framework for analysing spatial distribution of entrepreneurial activity. Ten interrelated EE-elements were applied to measure innovative entrepreneurship across 259 NUTS 2 regions in Europe. Considering the theoretical mobility of these ten elements, spillover effects across regions were ought to be happening. Therefore, the following research question was formulated: *What is the effect of EE resources of neighbouring regions on the EE performance of a focal region?*

To answer this research question seven hypotheses were formulated surrounding the theoretical mobility of seven resource elements. Three elements theoretically have no spillover potential and were used as control variables in this research. The seven hypotheses were tested using spatial regression models incorporating local elements with spatially lagged, 'neighbouring region', elements.

Based on the findings of this study, it appears that the effect of EE resources from neighbouring regions have a contradictory effect to what was originally anticipated. The empirical evidence challenges the original hypotheses on the positive effects of spatial spillover of resources. Specifically for Demand, Knowledge and Finance, having a high scoring neighbour was found to depress the performance of the EE of a focal region. This means the higher scoring neighbouring region might compete for resources or limit a focal region to capitalize on its resources, thus decreasing innovative entrepreneurial output. For the elements Talent, Intermediate, and Networks, the same significant negative effects were discovered, however these are disputed by several robustness checks, and therefore, need further research for validation. Lastly, this study found no indication of a significant spillover effect for Leadership, suggesting that this factor's influence might be more regional than thought, or just has no effect on this scale.

The additional analysis reveal additional insights into spillover dynamics of EEs. Interaction effect analysis indicates that while proximity to high-scoring regions on Intermediate can benefit regions with lower scores on the Intermediate variable, matching high scores has a negative effect on Innovative Entrepreneurship output. A similar effect is discovered for Leadership. Secondly, negative higher-scoring neighbour effects are confirmed through a 'better neighbour' dummy. Overall, these analyses underline that while for weaker regions presence of high-scoring neighbours can have certain benefits, the main story remains that innovative entrepreneurship is negatively affected if a neighbouring region outperforms the focal region on resources.

The findings of this study suggest that being neighbour of high-performing regions has negative effects on focal region EE performance, rather than the expected positive effect. The negative relationship between EE resources of neighbouring regions and the focal region's EE output might be an indicator of the concept of 'agglomeration shadows' in an entrepreneurial sense.

As social and economic differences in the world keep increasing, it is crucial to gain deeper understanding in how the dynamics of EEs work, thus fostering innovative entrepreneurship for progress in all regions. This research shed light on an untouched aspect of EEs, the spatial spillover effects. The anticipated effects were sought to be positive as spillovers mainly cause positive externalities, however a contrary effect was discovered. Strong neighbours might be more competitive than cooperative, potentially draining peripheral regions from their resources and entrepreneurs.

6. Discussion

The results show a contradictory story to what the seven hypotheses proposed, and therefore the hypotheses were rejected based on the empirical evidence. When exploring these new directions limitations and restrictions come up and these must be tackled during the research or with following research. However, this path also leads to useful contributions to academics and practice. The discussion surrounding implications, limitations and further research is elaborated upon in this chapter.

6.1 Theoretical implications

Theoretically, the EE-elements have been reassured to have a positive influence on innovative entrepreneurship (Leendertse et al., 2022; Stam & van de Ven, 2021). Furthermore, these elements have been extended with their effects on a spatial scale towards neighbouring regions. The insight that the presence of strong neighbouring regions in most EE-elements leads to negative performance of the focal region suggest some form of competition. This introduces the notion of an 'agglomeration shadow' when being proximate to high-performing regions.

Currently, EE theory is mainly applied through case studies and descriptive analyses, however, more attention is sought for quantitative and comparative applications (Alvedalen & Boschma, 2017). Therefore, this study adds to the applicability of EE theory by incorporating a quantitative analytical framework. The findings necessitates further theoretical exploration to find the underlying mechanisms driving the unexpected outcomes. Consequently, this study not only contributes to the theoretical development of the EE framework but also prompts new lines of inquiry in the field of spatial spillover theory, marking advancement in the theoretical understanding of these domains.

This study further opens the debate on the spatiality of EEs, providing additional perspectives on the understanding of EE boundaries. In agreement with Wurth et al. (2022), we confirm that ecosystem elements interact across all spatial scales, accentuating both local and spatial influences of resources across NUTS 2 regions. Malecki (2018) affirms that while entrepreneurship is inherently local, critical resources can stem from distant locations, thereby blurring traditional EE boundaries. The border of an EE may then be viewed not as a rigid line, but a gradient where the influence of the ecosystem reaches. This perception aligns with Fischer et al.'s (2022) theory that an ecosystem's reach is developed by its internal processes rather than by imposed political or administrative confines. We observe this phenomenon in our study, noting that the reach of the EE can extend beyond conventional boundaries due to the resource pull, possibly surpassing even NUTS 2 regions. This view can be used for new research to find the specific borders of EEs through quantitative spatial research.

Methodologically, this study is the first in the examination of spillover effects in an EE context using regression models. The regional effects of different resources on entrepreneurship has been widely covered, but now a new empirical foundation has been established for measuring interregional interactions of EEs. Now a wider lens can be applied when studying EE performance outside of considering the internal workings. This study opens the door towards further research to refine and expand findings on interaction effects between EEs.

Further improvements have been made towards indicators of the ten EE-elements. Knowledge, now represented by patents per capita, is a more direct approach to knowledge than R&D investments. Patents are the commercial outcome of inventions that created new knowledge (Archibugi & Pianta, 1996). They identify the output of R&D investments, therefore reinforcing the link between inputs and outputs (Mueller, 1966). Therefore, mapping the current knowledge base, patents appear more precise than R&D investments, as these do not guarantee increased knowledge. For Networks, a small improvement has been made by including an additional year in the variable. The chance that the variable is influenced by regions which had unique performance in one specific year is decreased and therefore the variable has more validity.

The field of spatial spillovers has often been criticized for a disproportionate emphasis on global models (Lesage, 2014), with much of the current research predominantly focusing on China, especially about economic development and industry agglomeration impacts on green economic efficiency (Li et al., 2022; Zeng et al., 2020). Although these studies offer valuable insights, the unique regional dynamics and context of Europe necessitate more localized spatial spillover studies to address its specific needs and challenges. This research bridges this gap by emphasizing the relevance of local spatial spillover effects in the European context. This study provides a valuable addition to research in Europe's spatial spillover field. It underscores the importance of understanding the regional interplay and cross-regional influences within Europe, which are important for formulating effective regional and transnational strategies to stay economically competitive, and even develop in more sustainable ways.

6.2 Practical implications

Besides the theoretical and methodological contributions, this research has practical and policy value. First, and foremost, this study challenges some traditional assumptions about positive spillover effects in EEs, suggesting that being nearby a high-performing region may rather inhibit than foster innovative entrepreneurial activities. Policymakers may use this insight to revise regional development strategies to retain resources and entrepreneurs within the region. The ten EE-elements all foster entrepreneurship. However, in this quantitative research in all the different models Intermediate and Leadership are the variables which consistently showed the largest effect sizes. Therefore, when targeting improving innovative entrepreneurial activities within a region policymakers should focus on these two elements as they encompass the largest impact. However, they should keep in mind that a good development of all ten elements is important for a well-performing EE. The focus of policymakers should be on the internal workings as external effects, such as the spillover effects, do not offer benefits based on our results.

The additional analysis, covering the interaction effects, uncovered a specific interaction which might favour underdeveloped EEs. Significant interaction effects were noted in the Intermediate and Leadership elements, which might benefit lower performing regions in these elements. For example, when a region has a low Intermediate score, indicating a lack of intermediary services, yet neighbours a well-performing region in this field, positive externalities in the form of spillovers arise. This outcome may favour policymakers in a strategic perspective. Regions encountering issues in developing their own Intermediates, may redirect resources towards other elements, as the shortcomings in Intermediate may be compensated through spillover effects.

6.3 Limitations

This research also encountered some limitations as part of the process of discovery. One primary consideration in this research was finding causality between neighbouring regions elements and focal region innovative entrepreneurship. This has not been proven before and that presented a challenge and opportunity for this research. In the following section various limitations are highlighted that might be potential avenues for future research.

Methodologically, there were different considerations and their limitations. First, the chosen level of analysis was NUTS 2. This is a proven applicable scale for quantitative analysis of EEs (Leendertse et al., 2022). However, NUTS 2 regions differ a lot in size, whereas Inner- Londen West-East (UKI3-4) spans 319 km2 and North and East Finland (FI1D) spans 203.475 km2. This size difference may influence spillover potential towards neighbouring regions. Because of the contingency-based spillover measure, these size differences are not incorporated when measuring the spillover potential. Thereby these large NUTS 2 areas might have no spillover effects due to the size, and this might influence the overall effectiveness of measuring the spillover effects over all regions. A distance-based spillover effect measure counters this by pointing out the distances the resource cover.

Second, a main limitation in this field of study is data availability, therefore, the data used for this study has mainly been replicated from Leendertse et al. (2022). While this replication offers more methodological consistency and boosts validity of the study, the limited data availability also has drawbacks. To start, causality is harder to control for as the indicators for the independent variables are measured in different periods ranging from 2013 (Talent) to 2019 (Intermediate). This negatively impacts the validity of the results. Furthermore, the used data is a heterogeneous set containing both indicators in percentages (for example of SMEs collaborating of total SMEs within a region) or absolute values per capita. When evaluating spillover effects, it is more useful to have a view of the values per capita as this is in line with the dependent variable which is also measured in innovative entrepreneurial firms per capita. This limitation is hard to surpass as there already is limited data available on these different elements covering all NUTS 2 regions in Europe. Applying more advanced data gathering techniques such as web scraping algorithms combined with geo-coding opens more possibilities on data availability.

Leadership, in our study, is measured by the innovation project leaders involved in Horizon 2020 projects. These projects often are by organizations seeking funding for their projects towards research and innovation, and typically located at the organizational headquarters. This does show a correlation with a higher local entrepreneurial output, this does not influence innovative entrepreneurship across NUTS 2 borders. Collaboration with these projects are often based on geographical proximity. As Wanzenböck et al. (2020) noted, partners with prior collaborative experiences on Horizon 2020 projects frequently continue to work together, thus fostering local accumulation of the Leadership variable. However, this does not appear to generate spillover effects. Therefore, adding Leadership indicators additionally to Horizon 2020 project leaders gives an overall better understanding of this elements, as the current indicator is quite specific.

Even though Crunchbase has been recognized as a valid database for innovative firms (Dalle et al., 2017; Leendertse et al., 2022), there might be some limitations to this measure. This data is mainly sourced from an investor network and community contributors, and therefore might be more complete on regions which contain the most active contributors. They currently have a large staff controlling the data; however, entries might lack (School et al., 2017). The measure of Crunchbase is an assumption-based indicator namely potential HGFs, therefore they are not proven HGFs. For higher reliability of the results other measures for innovative entrepreneurship could be researched using performance-based indicators like actual HGF occurrence.

Due to the limited data availability on the elements, only a current snapshot was produced of the entrepreneurial ecosystem inputs and output. EEs evolve (Brown & Mason, 2017), in the short term there are the empirically measured negative, potential competition, effects. In the long-term there might be positive spillover effects of having a strong neighbour, which might increase development potential. Future research in the form of a longitudinal analysis on spillover effects of EE-elements captures the effect of having strong neighbours on focal regions in the long run.

6.4 Further research

Several paths for further research already have been highlighted by implications and limitations. To extend on the limitations given, first, there is room for potential with the indicators which measure EE-elements. Current indicators are effective tools for analysis, however more detailed data refined to the specific elements could provide further insights. Second, the limitations and advantages of NUTS 2 analysis have already been highlighted. Further research could expand this analysis by focusing on smaller scales or different kind of regional divisions. NUTS 3 has been argued also as a respectable level of analysis and spillover effects might even become clearer on this level as geographical distances decrease. Third, future analysis could expand to different economies than Europe, to for example the USA or South-East Asia. Hereby comparative analyses could be made on how EE spillovers function in different cultural contexts. Furthermore, it could further validate the findings of this research. Fourth, given the limitation of the current data only providing a snapshot of the current spillover effects between EEs, a longitudinal study would give further insight into the temporal aspect of these effects. Hereby causal mechanisms can be discovered on how EEs evolve over time, with potential effects from neighbouring regions.

Earlier research established varying entrepreneurial activity in European countries (Brown & Mason, 2017). As visible in the figure 3 (section 4.1), nations such as the UK, the Netherlands and Scandinavia all have wide distributed high-performing regions. In contrast, East-South European countries have fewer medium to high scoring region, with many of the medium to high scoring regions containing their capital. These differences in country dynamics might relate to different spillover effects. For example, it could be possible that in the weaker performing countries all the entrepreneurial activity draws, or drains, towards the capital. While in the higher-performing countries the elements are better distributed throughout the country, enabling entrepreneurial activities all over. Discovering how spillover effects between regions differ between high-performing nations and those still developing offers an interesting avenue for research.

Finally, as these findings show that regions experience some kind of drain due to high-performing neighbouring regions, underscoring the need for research on how policy can influence these dynamics. The draining effects of stronger neighbours might be due to national policies focussing on high-performance regions or only on entrepreneurship in general, inadvertently supporting strong EEs that would benefit more than less-developed EEs. Furthermore, when regions start competing for national resources with stronger neighbours, this could result in them falling further behind (Bosma & Stam, 2012). The effects of national entrepreneurship policy on regional disparities in entrepreneurial activity represents an avenue for future research. It would be very valuable to examine how policy can mitigate these effects and cause more balanced, sustainable regional entrepreneurship and counteract a Winner-Takes-All effect to promote a balanced distribution of entrepreneurial activities across Europe.

Acknowledgements

I want to express large gratitude to my supervisors Dr. Frank van Rijnsoever and MSc Jip Leendertse for guiding me through the project and pushing me to dive into novel methods I had not encountered before. This sparked a greater interest in me for this subject. Furthermore, my thanks also go to Dr Janpieter van de Pol for feedback on my proposal and further guiding in the latter stages. Finally, I want to thank Merel de Kok, Robbert Messing, Ben Bresser and ChatGPT for being sparring partners during my research, and for proofreading my final thesis.

References

Acs, Z. J., Audretsch, D. B., & Lehmann, E. E. (2013). The knowledge spillover theory of entrepreneurship. *Small Business Economics*, *41*(4), 757–774. https://doi.org/10.1007/s11187-013-9505-9

Ács, Z. J., Autio, E., & Szerb, L. (2014). National Systems of Entrepreneurship: Measurement issues and policy implications. *Research Policy*, *43*(3), 476–494. https://doi.org/10.1016/j.respol.2013.08.016

Acs, Z. J., & Sanders, M. (2012). Patents, knowledge spillovers, and entrepreneurship. *Small Business Economics*, *39*(4), 801–817. https://doi.org/10.1007/s11187-011-9322-y

Acs, Z. J., Stam, E., Audretsch, D. B., & O'Connor, A. (2017). The lineages of the entrepreneurial ecosystem approach. *Small Business Economics*, *49*(1), 1–10. https://doi.org/10.1007/s11187-017-9864-8

Agarwal, R., Audretsch, D., & Sarkar, M. (2010). Knowledge spillovers and strategic entrepreneurship. *Strategic Entrepreneurship Journal*, *4*(4), 271–283. https://doi.org/https://doi.org/10.1002/sej.96

Alvedalen, J., & Boschma, R. (2017). A critical review of entrepreneurial ecosystems research: towards a future research agenda. *Https://Doi.Org/10.1080/09654313.2017.1299694*, *25*(6), 887–903. https://doi.org/10.1080/09654313.2017.1299694

Anselin, L., & Bera, A. K. (1998). Spatial Dependence in linear Regression Models with an Introduction to Spatial Econometrics. In *Handbook of Applied Economic Statistics*. CRC Press. https://doi.org/10.1201/9781482269901-36

Archibugi, D., & Pianta, M. (1996). Measuring technological change through patents and innovation surveys. *Technovation*, *16*(9), 451–519. https://doi.org/10.1016/0166-4972(96)00031-4

Arora, V., & Vamvakidis, A. (2005). THE IMPLICATIONS OF SOUTH AFRICAN ECONOMIC GROWTH FOR THE REST OF AFRICA. *South African Journal of Economics*, *73*(2), 229–242. https://doi.org/10.1111/J.1813-6982.2005.00015.X

Audretsch, D. B., & Belitski, M. (2017). Entrepreneurial ecosystems in cities: establishing the framework conditions. *Journal of Technology Transfer*, *42*(5), 1030–1051. https://doi.org/10.1007/S10961-016-9473-8/TABLES/4

Audretsch, D. B., Keilbach, M. C., & Lehmann, E. (2006). *Entrepreneurship and economic growth*. Oxford University Press.

Audretsch, D. B., & Lehmann, E. E. (2005). Does the knowledge spillover theory of entrepreneurship hold for regions? *Research Policy*, *34*(8), 1191–1202. https://doi.org/10.1016/j.respol.2005.03.012

Autant-Bernard, C., Billand, P., Frachisse, D., & Massard, N. (2007). Social distance versus spatial distance in R&D cooperation: Empirical evidence from European collaboration choices in micro and nanotechnologies*. *Papers in Regional Science*, *86*(3), 495–519. https://doi.org/10.1111/J.1435-5957.2007.00132.X

Autio, E., Kenney, M., Mustar, P., Siegel, D., & Wright, M. (2014). Entrepreneurial innovation: The importance of context. *Research Policy*, *43*(7), 1097–1108. https://doi.org/10.1016/J.RESPOL.2014.01.015

Autio, E., Nambisan, S., Thomas, L. D. W., & Wright, M. (2018). Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal*, *12*(1), 72–95. https://doi.org/10.1002/sej.1266

Backman, M., & Karlsson, C. (2017). Location of New Firms: Influence of Commuting Behaviour. *Growth and Change*, *48*(4), 682–699. https://doi.org/10.1111/GROW.12200

Bartlett, J. W. ., & Economy, P. (2002). *Raising Capital For Dummies - Joseph W. Bartlett, Peter Economy - Google Books*. John Wiley & Sons.

Baumol, W. J. (1990). Entrepreneurship: Productive, Unproductive, and Destructive. *Journal of Political Economy*, *98*(5), 893–921. http://www.jstor.org.proxy.library.uu.nl/stable/2937617

Baumol, W. J. (2010). *The Microtheory of Innovative Entrepreneurship*. Princeton University Press. https://doi.org/10.1515/9781400835225

Baumont, C., Ertur, C., & Le Galle, J. (2001). *A spatial econometric analysis of geographic spillovers and growth for European regions, 1980-1995*. 26 p., ref. bib. : 2 p. https://hal.science/hal-01526858

Bivand, R. S., Pebesma, E., & Gómez-Rubio, V. (2013). *Applied Spatial Data Analysis with R* (Second edition). http://www.springer.com/series/6991

Blum, U., Haynes, K. E., & Karlsson, C. (1997). Introduction to the special issue The regional and urban effects of high-speed trains. *Ann Reg Sci*, *31*(1), 1–20.

Bosma, N., & Stam, E. (2012). Local Policies for High-Employment Growth Enterprises 'High-growth firms: local policies and local determinants'. *Report Prepared for the OECD/DBA International Workshop on "High-Growth Firms: Local Policies and Local Determinants"* .

Bosma, N., & Sternberg, R. (2014). Entrepreneurship as an Urban Event? Empirical Evidence from European Cities. *Https://Doi.Org/10.1080/00343404.2014.904041*, *48*(6), 1016–1033. https://doi.org/10.1080/00343404.2014.904041

Bramwell, A., Hepburn, N., & Wolfe, D. A. (2019). Growing entrepreneurial ecosystems: Public intermediaries, policy learning, and regional innovation. *Journal of Entrepreneurship and Public Policy*, *8*(2), 272–292. https://doi.org/10.1108/JEPP-04-2019-0034/FULL/PDF

Brown, R., & Mason, C. (2017). Looking inside the spiky bits: a critical review and conceptualisation of entrepreneurial ecosystems. *Small Business Economics*, *49*(1), 11–30. https://doi.org/10.1007/s11187-017-9865-7

Bruns, K., Bosma, N., Sanders, M., & Schramm, M. (2017). Searching for the existence of entrepreneurial ecosystems: a regional cross-section growth regression approach. *Small Business Economics*, *49*(1), 31–54. https://doi.org/10.1007/s11187-017-9866-6

Burger, M. J., Meijers, E. J., Hoogerbrugge, M. M., & Tresserra, J. M. (2014). Borrowed Size, Agglomeration Shadows and Cultural Amenities in North-West Europe. *Https://Doi.Org/10.1080/09654313.2014.905002*, *23*(6), 1090–1109. https://doi.org/10.1080/09654313.2014.905002

Capello, R. (2009). Spatial spillovers and regional growth: A cognitive approach. *European Planning Studies*, *17*(5), 639–658. https://doi.org/10.1080/09654310902778045

Casella, G., & Berger, R. L. (2002). *Statistical lnference* (Second). Duxbury Thomson Learning. www.duxbury.com

Castaño, M. S., Méndez, M. T., & Galindo, M. Á. (2015). The effect of social, cultural, and economic factors on entrepreneurship. *Journal of Business Research*, *68*(7), 1496–1500. https://doi.org/10.1016/j.jbusres.2015.01.040

Cavallo, A., Ghezzi, A., & Rossi-Lamastra, C. (2021). Small-medium enterprises and innovative startups in entrepreneurial ecosystems: exploring an under-remarked relation. *International Entrepreneurship and Management Journal*, *17*(4), 1843–1866. https://doi.org/10.1007/S11365-020-00698-3/TABLES/8

CFI Team. (2022, November 7). *Spillover Effect - Overview, Types, Positive and Negative Effects*. https://corporatefinanceinstitute.com/resources/economics/spillover-effect/

Coe, D. T. (1993). International R&D Spillovers. *NBER Working Paper Series, No. 4444*.

Cooper, A. C., Gimeno-Gascon, F. J., & Woo, C. Y. (1994). Initial human and financial capital as predictors of new venture performance. *Journal of Business Venturing*, *9*(5), 371–395. https://doi.org/10.1016/0883-9026(94)90013-2

Cortinovis, N., & van Oort, F. (2019). Between spilling over and boiling down: network-mediated spillovers, local knowledge base and productivity in European regions. *Journal of Economic Geography*, *19*(6), 1233–1260. https://doi.org/10.1093/JEG/LBY058

Coxe, S., West, S. G., & Aiken, L. S. (2009). The Analysis of Count Data: A Gentle Introduction to Poisson Regression and Its Alternatives. *Journal of Personality Assessment*, *91*(2), 121–136. https://doi.org/10.1080/00223890802634175

Dalle, J., den Besten, M., & Menon, C. (2017). *Using Crunchbase for economic and managerial research* (No. 2017/0; OECD Science, Technology and Industry Working Papers).

Dubé, J., & Legros, D. (2014). Spatial Autocorrelation. *Spatial Econometrics Using Microdata*, 59–91. https://doi.org/10.1002/9781119008651.CH3

El-Dardiry, R., & Vogt, B. (2022). How Far Do Gazelles Run? Growth Patterns of Regular Firms, High Growth Firms and Startups. In *CPB Netherlands Bureau for Economic Policy Analysis* (No. 432). https://doi.org/10.34932/tna2-rr44

Ellison, G., Glaeser, E. L., Kerr, W., & Center, R. (2007). *What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns*. http://www.nber.org/papers/w13068

Ertur, C., & Koch, W. (2007). Growth, technological interdependence and spatial externalities: theory and evidence. *Journal of Applied Econometrics*, *22*(6), 1033–1062. https://doi.org/10.1002/JAE.963

EUROSTAT. (n.d.). *Background - NUTS - Nomenclature of territorial units for statistics - Eurostat*. 2021. Retrieved 17 January 2023, from https://ec.europa.eu/eurostat/web/nuts/background

EUROSTAT. (2007). *OECD Manual on Business Demography Statistics*.

Feldman, M. P. (2014). The character of innovative places: Entrepreneurial strategy, economic development, and prosperity. *Small Business Economics*, *43*(1), 9–20. https://doi.org/10.1007/S11187-014-9574-4/METRICS

Fingleton, B., & López-Bazo, E. (2006). Empirical growth models with spatial effects. *Papers in Regional Science*. https://doi.org/10.1111/j.1435-5957.2006.00074.x

Fischer, B., Meissner, D., Vonortas, N., & Guerrero, M. (2022). Spatial features of entrepreneurial ecosystems. *Journal of Business Research*, *147*, 27–36. https://doi.org/10.1016/j.jbusres.2022.04.018

Fischer, M., Scherngell, T., & Jansenberger, E. (2006). The Geography of Knowledge Spillovers Between High-Technology Firms in Europe: Evidence from a Spatial Interaction Modeling Perspective. *Geographical Analysis*, *38*(3), 288–309. https://doi.org/10.1111/J.1538-4632.2006.00687.X

Florax, R., & Folmer, H. (1992). Specification and estimation of spatial linear regression models: Monte Carlo evaluation of pre-test estimators. *Regional Science and Urban Economics*, *22*(3), 405–432. https://doi.org/10.1016/0166-0462(92)90037-2

Fraiberg, S. (2017). Start-Up Nation: Studying Transnational Entrepreneurial Practices in Israel's Start-Up Ecosystem. *Journal of Business and Technical Communication*, *31*(3), 350–388. https://doi.org/10.1177/1050651917695541

Frederiksen, L., Practice, K. W.-… T. and, & 2016, undefined. (2016). Mobility and entrepreneurship: Evaluating the scope of knowledge–based theories of entrepreneurship. *Journals.Sagepub.Com*, *40*(2), 359–380. https://doi.org/10.1111/etap.12223

Goswami, K., Mitchell, | J Robert, Suresh Bhagavatula, |, Correspondence, K., & Goswami, R. (2018). Accelerator expertise: Understanding the intermediary role of accelerators in the development of the Bangalore entrepreneurial ecosystem. *Strategic Entrepreneurship Journal*, *12*(1), 117–150. https://doi.org/10.1002/SEJ.1281

Granovetter, M. (1983). The Strength of Weak Ties: A Network Theory Revisited. *Sociological Theory*, *1*, 201. https://doi.org/10.2307/202051

Grilo, I., & Thurik, R. (2004). *Determinants Of Entrepreneurship In Europe*. www.erim.eur.nl

Haveman, R. H., & Wolfe, B. L. (2002). Social and nonmarket benefits from education in an advanced economy. *Conference Series ; [Proceedings]*, *47*(Jun), 97–142. https://ideas.repec.org/a/fip/fedbcp/y2002ijunp97-142n47.html

Hunt, J. G. (Jerry). (2004). What is leadership? In *The nature of leadership.* (pp. 19–47). Sage Publications, Inc. https://doi.org/10.1177/0018726701544004

Hutchinson, E. (2017). *Principles of Microeconomics (Uvic)*. https://openlibrary-repo.ecampusontario.ca/jspui/handle/123456789/355

Invest Europe. (2019). *Activity report 2019*.

Isenberg, D. (2011). *The Entrepreneurship Ecosystem Strategy as a New Paradigm for Economic Policy: Principles for Cultivating Entrepreneurship 1*.

Lee, S. Y., Florida, R., & Acs, Z. (2004). *Regional Studies Creativity and Entrepreneurship: A Regional Analysis of New Firm Formation*. https://doi.org/10.1080/0034340042000280910

Leendertse, J., Schrijvers, M., & Stam, E. (2022). Measure Twice, Cut Once: Entrepreneurial Ecosystem Metrics. *Research Policy*, 104336. https://doi.org/10.1016/J.RESPOL.2021.104336

Lesage, J. P. (2014). *Electronic copy available at: http://ssrn.com/abstract=2420725 What regional scientists need to know about spatial econometrics*. http://ssrn.com/abstract=2420725at:https://ssrn.com/abstract=2420725Electroniccopyavailableat :http://ssrn.com/abstract=2420725

LeSage, J., & Pace, R. (2009). *Introduction to spatial econometrics*. Chapman and Hall/CRC. https://doi.org/10.4000/rei.3887

Li, S., Ren, T., Jia, B., & Zhong, Y. (2022). The Spatial Pattern and Spillover Effect of the Eco-Efficiency of Regional Tourism from the Perspective of Green Development: An Empirical Study in China. *Forests 2022, Vol. 13, Page 1324*, *13*(8), 1324. https://doi.org/10.3390/F13081324

López-Bazo, E., Vayá, E., & Artís, M. (2004). Regional externalities and growth: Evidence from European regions. *Journal of Regional Science*, *44*(1), 43–73. https://doi.org/10.1111/j.1085-9489.2004.00327.x

Malecki, E. J. (2018). Entrepreneurship and entrepreneurial ecosystems. *Geography Compass*, *12*(3). https://doi.org/10.1111/gec3.12359

Mason, C., & Brown, R. (2014). *Entrepreneurial ecosystems and growth oriented entrepreneurship*.

Mas-Verdu, F., Soriano, D. R., & Dobon, S. R. (2010). Regional development and innovation: The role of services. *Service Industries Journal*, *30*(5), 633–641. https://doi.org/10.1080/02642060802398085

Meijers, E. J., & Burger, M. J. (2017). Stretching the concept of 'borrowed size'. *Urban Studies*, *54*(1), 269–291. https://doi.org/10.1177/0042098015597642

Meijers, E. J., Burger, M. J., & Hoogerbrugge, M. M. (2015). *Borrowing size in networks of cities: City size, network connectivity and metropolitan functions in Europe* *. https://doi.org/10.1111/pirs.12181

Moreno, R., Paci, R., & Usai, S. (2005). Spatial Spillovers and Innovation Activity in European Regions. *Environment and Planning A: Economy and Space*, *37*(10), 1793–1812. https://doi.org/10.1068/a37341

Moriset, B., & Malecki, E. J. (2009). Organization versus Space: The Paradoxical Geographies of the Digital Economy. *Geography Compass*, *3*(1), 256–274. https://doi.org/10.1111/J.1749-8198.2008.00203.X

Mueller, D. C. (1966). Patents, Research and Development, and the Measurement of Inventive Activity. *The Journal of Industrial Economics*, *15*(1), 26. https://doi.org/10.2307/2097846

Mukesh, H., & Thomas, B. (2016). Individuality of Transnational Entrepreneurs: A Missing Link. *Bonfring International Journal of Industrial Engineering and Management Science*, *6*(3). https://doi.org/10.9756/BIJIEMS.8140

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., & Giovannini, E. (2005). *Handbook on Constructing Composite Indicators : Methodology and User Guide | OECD Statistics Working Papers* . https://www.oecd-ilibrary.org/economics/handbook-on-constructing-composite-indicators_533411815016

Nelson, R. (1981). Research on Productivity Growth and Productivity Differences: Dead Ends and New Departures. *Journal of Economic Literature*, *19*(3), 1029–1064. https://EconPapers.repec.org/RePEc:aea:jeclit:v:19:y:1981:i:3:p:1029-64

Normann, R. (2013). Regional Leadership: A Systemic View. *Systemic Practice and Action Research*, *26*(1), 23–38. https://doi.org/10.1007/S11213-012-9268-2/TABLES/2

North, D. C. (1955). Location Theory and Regional Economic Growth. *Source: Journal of Political Economy*, *63*(3), 243–258. https://www.jstor.org/stable/1825076?seq=1&cid=pdf-

NUTS - GISCO - Eurostat. (n.d.). Retrieved 20 June 2023, from https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts#nuts16

O'Connor, A., & Audretsch, D. (2022). Regional entrepreneurial ecosystems: learning from forest ecosystems. *Small Business Economics*. https://doi.org/10.1007/s11187-022-00623-8

OECD. (2009). *How Regions Grow*. OECD. https://doi.org/10.1787/9789264039469-en

OECD. (2011). *Entrepreneurship at a Glance 2011*. OECD. https://doi.org/10.1787/9789264097711-en

OECD. (2022). *REGPAT DATABASE*.

Ortega-Argilés, R., Komlósi, É., Acs, Z., Autio, E., & Szerb, L. (2014). *REDI, the regional entrepreneurship and development index : measuring regional entrepreneurship : final report*. European Comission Publications Office. https://doi.org/doi/10.2776/79241

Pike, A., Rodriguez-Pose, A., & Tomaney, J. (2016). *Local and Regional Development*. Routledge.

Qian, H. (2018). Knowledge-Based Regional Economic Development: A Synthetic Review of Knowledge Spillovers, Entrepreneurship, and Entrepreneurial Ecosystems. *Economic Development Quarterly*, *32*(2), 163–176. https://doi.org/10.1177/0891242418760981

Qian, H., Acs, Z. J., & Stough, R. R. (2013). Regional systems of entrepreneurship: The nexus of human capital, knowledge and new firm formation. *Journal of Economic Geography*, *13*(4), 559–587. https://doi.org/10.1093/JEG/LBS009

R Core Team. (2013). *R: A language and environment for statistical computing.* http://www.R-project.org/.

Sautet, F. (2013). Local and systemic entrepreneurship: Solving the puzzle of entrepreneurship and economic development. *Entrepreneurship: Theory and Practice*, *37*(2), 387–402. https://doi.org/10.1111/j.1540-6520.2011.00469.x

Schäfer, S. (2021). Spatialities of entrepreneurial ecosystems. *Geography Compass*, *15(9)*(e12591.).

Schäfer, S., & Henn, S. (2018). The evolution of entrepreneurial ecosystems and the critical role of migrants. A Phase-Model based on a Study of IT startups in the Greater Tel Aviv Area. *Cambridge Journal of Regions, Economy and Society*, *11*(2), 317–333. https://doi.org/10.1093/cjres/rsy013

School, B. B., Kemeny, T., Nathan, M., & Almeer, B. (2017). Using Crunchbase to explore innovative ecosystems in the US and UK. *Discussion Paper Series*.

Schrijvers, M., Stam, E., & Bosma, N. (2021). Figuring it out: Configurations of high-performing entrepreneurial ecosystems in Europe. *U.S.E. Working Paper Series*, *21*(5). https://dspace.library.uu.nl/handle/1874/419996

Spigel, B. (2017). The Relational Organization of Entrepreneurial Ecosystems. *Entrepreneurship: Theory and Practice*, *41*(1), 49–72. https://doi.org/10.1111/etap.12167

Spigel, B., & Harrison, R. (2018). Toward a process theory of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal*, *12*(1), 151–168. https://doi.org/10.1002/sej.1268

Stam, E. (2012). *Ambitious entrepreneurship : a review of the academic literature and new directions for public policy*. Advisory Council for Science and Technology Policy, AWT.

Stam, E. (2015). Entrepreneurial Ecosystems and Regional Policy: A Sympathetic Critique. *European Planning Studies*, *23*(9), 1759–1769. https://doi.org/10.1080/09654313.2015.1061484

Stam, E., & van de Ven, A. (2021). Entrepreneurial ecosystem elements. *Small Business Economics*, *56*(2), 809–832. https://doi.org/10.1007/S11187-019-00270-6/FIGURES/4

Szabo, Z. K., & Herman, E. (2012). Innovative Entrepreneurship for Economic Development in EU. *Procedia Economics and Finance*, *3*, 268–275. https://doi.org/10.1016/S2212-5671(12)00151-7

Tobler, W. R. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography*, *46*, 234. https://doi.org/10.2307/143141

van Rijnsoever, F. J. (2020). Meeting, mating, and intermediating: How incubators can overcome weak network problems in entrepreneurial ecosystems. *Research Policy*, *49*(1), 103884. https://doi.org/10.1016/J.RESPOL.2019.103884

Vega, S. H., & Elhorst, J. P. (2015). THE SLX MODEL. *Journal of Regional Science*, *55*(3), 339–363. https://doi.org/10.1111/jors.12188

Wanzenböck, I., Lata, R., & Ince, D. (2020). Proposal success in Horizon 2020: A study of the influence of consortium characteristics. *Quantitative Science Studies*, *1*(3), 1136–1158. https://doi.org/10.1162/QSS_A_00067

World Economic Forum. (2014). *Entrepreneurial Ecosystems Around the Globe and Early-Stage Company Growth Dynamics – the Entrepreneur's Perspective*.

Wurth, B., Stam, E., & Spigel, B. (2022). Toward an Entrepreneurial Ecosystem Research Program. *Entrepreneurship: Theory and Practice*, *46*(3), 729–778. https://doi.org/10.1177/1042258721998948

Yan, Z., & Li, H. (2010). Innovation search of new ventures in a technology cluster: the role of ties with service intermediaries. *Strategic Management Journal*, *31*(1), 88–109. https://doi.org/10.1002/SMJ.806

Zeng, G., Geng, C., & Guo, H. (2020). Spatial Spillover Effect of Strategic Eemerging Industry Agglomeration and Green Economic Efficiency in China. *Polish Journal of Environmental Studies*, *29*(5), 3901–3914. https://doi.org/10.15244/PJOES/116443

Appendix A: Variables and indicators extended

Five independent variables

Demand variable

Demand is an important driver as it shows societies' need for entrepreneurial activities, furthermore society needs to encompass the ability to purchase goods and services for entrepreneurial activities to be successful. Like Leendertse et al. (2022) three indicators from the RCI (Annoni & Dijkstra, 2019) have been used to measure the demand variable. These three indicators are disposable income as a measure of consumer demand, potential market size expressed in GRP and as final measure potential market size through population size compared to EU avg.

Talent variable

Talent has been extensively linked to entrepreneurship but is a broad concept as it encompasses the skills, knowledge, and experience of individuals (Stam & van de Ven, 2021). Therefore, multiple indicators are required to measure the talent variable. Some general human capital indicators are share of the population with tertiary education (OECD, 2009) and lifelong learning as this shows eagerness to improve themselves and enables individuals to keep up with latest developments (Laal & Salamati, 2012). Furthermore, for entrepreneurial talent e-skills and the amount of incorporation of SME creation/management training in education have been included.

Intermediary services variable

Intermediary services can enable entrepreneurial activities by providing access to a wide range of resources. Yan & Li (2010) provide many service examples such as structuring established or emerging businesses, navigating complex tax and legal issues, sourcing technology solutions, providing investment services, and accessing strategic advice. Like Stam and Van de Ven (2021) a general measure is the percentage of business service firms in the business population. Leendertse et al. (2022) measures this through percentage of employment in a region in knowledge-intensive market services. For this research the same measure was used. Leendertse et al. (2022) calculated a specific measure for entrepreneurial intermediate services through the number of incubators per capita, which was also utilized for this research.

Leadership variable

Leadership is an important variable as it provides guidance and direction for collective action in the EE (Stam & van de Ven, 2021). Entrepreneurial leaders come in many different types, transformational, team-oriented, or value-based, but they all are similar in carrying the task of mobilising towards a certain new idea (Gupta et al., 2004). This research has used the number of innovation project leaders of Horizon 2020 projects as indicator for Leadership, as used by Leendertse et al. (2022).

Finance variable

Finance helps entrepreneurs seize new possibilities and develop (Bartlett & Economy, 2002; Cooper et al., 1994). Venture capital is an indicator for entrepreneurial finance. Venture capital and high-potential entrepreneurship promote economic growth (Lerner, 2010). Venture capital is calculated by the average five-year venture capital spent by private equity investors per capita, which can be spent locally or globally (Leendertse et al., 2022).

The structural elements

Culture variable

Culture shapes norms that influence entrepreneurial practices and societal views on entrepreneurship, which in turn affect an individual's motivation to become an entrepreneur. Multiple different indicators are named in research for measuring culture, and in specific culture that influences entrepreneurship (Credit et al., 2018). First as a specific entrepreneurial culture indicator, the Global Entrepreneurship Monitor (GEM, 2018) researched how highly successful entrepreneurs are regarded and the extent to which self-employment is accepted as a feasible profession. These two indicators from GEM are included in this variable. Second, the cultural indicators related to trust and the perceived importance of creativity and innovation within the population are included, based on the European Social Survey (Leendertse et al., 2022).

Formal institutions variable

Formal institutions, consisting of legally mandated and socially accepted norms, laws, and supporting organisations or entities, help to organise and control social behaviour while setting boundaries for entrepreneurship. Measuring formal institutions is conducted through generic and entrepreneurship specific indicators. General measures come from the Quality of Government (QoG) study, which is a reliable source for institutional quality composed of three components: corruption, accountability, and impartiality. Entrepreneurial specific formal institutions are measured through the Ease of Doing Business Index (EDBI) which is a composite indicator based on seven elements. These two different measurements for formal institutions combine towards a total measure of formal institutions regarding entrepreneurship (Leendertse et al., 2022).

Physical infrastructure variable

Physical infrastructure as an important factor for entrepreneurship includes the internet, transportation, and information infrastructure to enable economic interactions (Audretsch et al., 2015). Leendertse et al. (2022) includes physical infrastructure indicators such as accessibility by road, accessibility by railway and number of passenger flights. Furthermore, the additional measure of percentage of households with internet access was added as a digital infrastructure measure.

Appendix B: Original indicators Networks & Knowledge

Original indicators Knowledge and Networks

	Dependent variable: Innovative Entrepreneurship		
	Independent variables:		
	Control model	Knowledge	Networks
Internal Structure	2.079***	2.176***	2.088***
	(0.169)	(0.193)	(0.209)
Local independent variable		0.082	**0.159***
		(0.055)	(0.085)
Max lagged variable		**-0.105*****	**-0.181***
		(0.032)	(0.092)
Constant	1.228***	1.269***	1.381***
	(0.231)	(0.255)	(0.268)
Observations	259	259	259
Adjusted R^2	**0.368**	**0.391**	**0.373**
Residual Std. Error	0.795 (df = 257)	0.781 (df = 255)	0.792 (df = 255)
F Statistic	150.958*** (df = 1; 257)	56.113*** (df = 3; 255)	52.216*** (df = 3; 255)
Note:			*p<0.1; **p<0.05; ***p<0.01

Model performance and comparison to the new indicators

The models display no issues with multicollinearity and heteroscedasticity The R-squared values demonstrate an improvement compared to the control model, rising to 0.391 for knowledge and 0.373 for networks. However, the models utilizing the newly discovered indicators yielded better results, with R-squared values of 0.422 for knowledge and 0.375 for networks. The minor improvement observed for networks is expected, compared to the larger for Knowledge, as this indicator mirrors the previous one but extends its range by one year to increase consistency. For Knowledge, the local effect is not significant with the original indicators, while the new indicators do return significant, indicating a positive correlation with innovative entrepreneurship. Similarly, for Networks, the effect holds a significance level of $p<0.1$ with the original indicators, but this improved to $p<0.05$ with the new ones. This suggests that both new indicators mark an enhancement on the original variables, ensuring more robust results.

Appendix C: Correlation matrix & description

	Mean	S.D.	D1	H1	H2	H3	H4	H5	H6	H7	C1	C2	C3	LH1	LH2	LH3	LH4	LH5	LH6	LH7
D1: Innovative Entrepreneurship	4	1	**1**	**0.39**	**0.57**	**0.74**	**0.41**	**0.63**	**0.54**	**0.42**	**0.61**	**0.44**	**0.71**	**0.15**	**0.42**	**0.14**	0.10	**0.22**	**0.30**	**0.30**
H1: Demand	4	1		**1**	**0.32**	**0.41**	**0.42**	**0.26**	**0.63**	**0.45**	**0.61**	**0.16**	**0.61**	**0.8**	**0.29**	**0.34**	**0.4**	**0.32**	**0.53**	**0.44**
H2: Talent	4	1			**1**	**0.43**	**0.34**	**0.41**	**0.7**	**0.71**	**0.81**	**0.19**	**0.76**	**0.25**	**0.83**	**0.37**	**0.25**	**0.39**	**0.56**	**0.58**
H3: Intermediate	4	1				**1**	**0.39**	**0.65**	**0.44**	**0.36**	**0.42**	**0.61**	**0.69**	**0.14**	**0.28**	**0.23**	0.02	**0.17**	**0.21**	**0.24**
H4: Knowledge	4	1					**1**	**0.43**	**0.51**	**0.17**	**0.46**	**0.19**	**0.57**	**0.25**	**0.25**	0.05	**0.34**	0.10	**0.36**	**0.17**
H5: Leadership	4	1						**1**	**0.37**	**0.31**	**0.35**	**0.39**	**0.66**	0.05	**0.25**	0.08	0.01	**0.14**	**0.19**	**0.23**
H6: Finance	4	1							**1**	**0.55**	**0.79**	**0.15**	**0.75**	**0.54**	**0.62**	**0.38**	**0.48**	**0.40**	**0.77**	**0.49**
H7: Networks	4	1								**1**	**0.64**	0.07	**0.67**	**0.43**	**0.63**	**0.38**	**0.22**	**0.47**	**0.44**	**0.82**
C1: Internal structure	1.3	0.29									**1**	0.09	**0.83**	**0.52**	**0.72**	**0.41**	**0.41**	**0.38**	**0.69**	**0.56**
C2: Capital	0.11	0.32										**1**	**0.35**	**-0.15**	-0.01	**0.15**	**-0.14**	-0.03	-0.09	-0.04
C3: EE-index	9.2	6.5											**1**	**0.41**	**0.60**	**0.45**	**0.29**	**0.40**	**0.53**	**0.54**
LH1: Demand	4.5	0.9												**1**	**0.38**	**0.42**	**0.53**	**0.41**	**0.67**	**0.54**
LH2: Talent	4.4	0.96													**1**	**0.42**	**0.38**	**0.50**	**0.70**	**0.66**
LH3: Intermediate	4.6	1.3														**1**	**0.34**	**0.62**	**0.44**	**0.38**
LH4: Knowledge	4.7	1.6															**1**	**0.49**	**0.58**	**0.31**
LH5: Leadership	4.8	1.3																**1**	**0.49**	**0.51**
LH6: Finance	4.4	0.92																	**1**	**0.54**
LH7: Networks	4.4	0.91																		**1**

** All values in bold are significant at 5%*

Appendix D: Removed outlier models

Removed outlier spatial models

	Dependent variable: Innovative Entrepreneurship							
	Independent variables							
	Control model	Demand	Talent	Intermediate	Knowledge	Leadership	Finance	Networks
Internal Structure	1.966***	2.044***	1.459***	1.106***	1.938***	1.481***	1.852***	1.903***
	(0.166)	(0.195)	(0.276)	(0.148)	(0.192)	(0.153)	(0.260)	(0.216)
Local independent variable		0.371***	0.408***	0.747***	0.185***	0.475***	0.382***	0.195**
		(0.081)	(0.101)	(0.051)	(0.058)	(0.049)	(0.085)	(0.092)
Max lagged variable		-0.526***	-0.263***	-0.016	-0.118***	0.035	-0.421***	-0.209**
		(0.084)	(0.091)	(0.050)	(0.039)	(0.038)	(0.079)	(0.093)
Constant	1.360***	2.140***	1.553***	-0.376	1.201***	-0.037	1.857***	1.589***
	(0.226)	(0.255)	(0.241)	(0.254)	(0.254)	(0.250)	(0.239)	(0.263)
Observations	256	256	256	256	256	256	256	256
	0.355	0.442	0.395	0.648	0.393	0.541	0.430	0.369
Adjusted R^2	0.352	0.436	0.387	0.644	0.386	0.536	0.423	0.361
Residual Std. Error	0.767 (df = 254)	0.716 (df = 252)	0.746 (df = 252)	0.569 (df = 252)	0.747 (df = 252)	0.650 (df = 252)	0.724 (df = 252)	0.762 (df = 252)
F Statistic	139.721*** (df = 1; 254)	66.590*** (df = 3; 252)	54.737*** (df = 3; 252)	154.897*** (df = 3; 252)	54.498*** (df = 3; 252)	99.125*** (df = 3; 252)	63.349*** (df = 3; 252)	49.081*** (df = 3; 252)
Note:								*p<0.1; **p<0.05; ***p<0.01

Model performance

The models show no issues regarding multicollinearity or heteroscedasticity. This marks an instance in this study where heteroscedasticity was absent, this could be attributed to the removal of these outliers. The removal of these three outliers only led to one change in the results, rendering effect of neighbouring Intermediate non-significant. This suggests that the original significance of the Intermediate variable might have been driven by the extreme value in UKI3-4. All other variable effects remained consistent with the results presented in section 4.3, indicating the robustness of these findings.

Appendix E: Spatial weight matrix summary

Spatial weight matrix

Weight matrix	**W**
Type	Contingency
Normalization	Row
Dimension	259 x 259
Neighbours	
Minimum	1
Mean	4.58
Maximum	11

Number of neighbours per region.

Number of links	**Amount of regions**
1	15
2	20
3	40
4	46
5	59
6	40
7	26
8	9
9	3
11	1

Appendix F: Additional linkages models

Additional linkages models

	Dependent variable: Innovative Entrepreneurship							
	Independent variables							
	Control model	Demand	Talent	Intermediate	Knowledge	Leadership	Finance	Networks
Internal Structure	2.079***	2.132***	1.525***	1.427***	2.015***	1.512***	1.870***	2.004***
	(0.169)	(0.203)	(0.284)	(0.144)	(0.194)	(0.161)	(0.273)	(0.220)
Local independent variable		0.344***	0.387***	0.600***	0.194***	0.474***	0.354***	0.172*
		(0.083)	(0.106)	(0.039)	(0.055)	(0.044)	(0.092)	(0.096)
Max lagged variable		-0.477***	-0.218**	-0.118***	-0.108***	-0.001	-0.343***	-0.173*
		(0.087)	(0.093)	(0.030)	(0.033)	(0.035)	(0.087)	(0.098)
Constant	1.228***	1.935***	1.373***	0.240	1.043***	0.092	1.623***	1.403***
	(0.231)	(0.268)	(0.246)	(0.195)	(0.249)	(0.235)	(0.254)	(0.272)
Observations	259	259	259	259	259	259	259	259
Adjusted R^2	0.368	0.430	0.394	0.671	0.408	0.562	0.409	0.372
Residual Std. Error	0.795 (df = 257)	0.755 (df = 255)	0.778 (df = 255)	0.574 (df = 255)	0.769 (df = 255)	0.662 (df = 255)	0.769 (df = 255)	0.793 (df = 255)
F Statistic	150.958*** (df = 1; 257)	65.775*** (df = 3; 255)	56.987*** (df = 3; 255)	176.414*** (df = 3; 255)	60.288*** (df = 3; 255)	111.475*** (df = 3; 255)	60.553*** (df = 3; 255)	51.851*** (df = 3; 255)
Note:								*p<0.1; **p<0.05; ***p<0.01

Additional regional connections across (short) waterbodies are possible due to ferries and tunnels. The three connections contain two ferries of 2 hours connecting different countries and the Eurotunnel connecting France and the UK. The connected regions in question are: Eesti (EE00) and Helsinki-Uusimaa (FI1B), Southern Scotland (UKM9) and Northern Ireland (UKN0), Kent (UKJ4) and Nord-Pas de Calais (FRE1). These additional linkages increase the total number of links from 1186 to 1192. For this to make a statistical impact a very heavy effect needs to be present. In this case this effect is absent.

Model performance

No multicollinearity issues were discovered, the Intermediate contained heteroscedasticity, while all other models showed no heteroscedasticity issues. The remaining results are like section 4.3.

Appendix G: EEI models

EEI regression model

	Dependent variable:	
	Innovative Entrepreneurship	
	(1)	(2)
Local EEI	0.097^{***}	0.105^{***}
	(0.007)	(0.011)
Capital	0.705^{***}	0.641^{***}
	(0.143)	(0.156)
Max lagged EEI		-0.009
		(0.009)
Constant	3.032^{***}	3.074^{***}
	(0.073)	(0.085)
Observations	259	259
Adjusted R^2	0.539	0.539
Residual Std. Error	0.679 (df = 256)	0.679 (df = 255)
F Statistic	152.018^{***} (df = 2; 256)	101.694^{***} (df = 3; 255)
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Model performance

Model 1 shows a model with high explanatory power, as 54% of the output is explained by just the local EEI and capital status. The VIF-test indicated a maximum VIF of 2.6, meaning that there was no multicollinearity present. The BP-test came back significant. This indicates that there is heteroscedasticity present. Both EEI and Capital effects are significant and positive indicating higher innovative entrepreneurial output if the focal region is higher on the EEI and/or a capital region. Model 2 shows no improvement in the adjusted R squared when adding the lagged EEI and therefore there is no improvement to model 1. The effect of the neighbouring EEI is non-significant which indicates that there is no effect on the focal region based on EEI value. This calls for further investigation into the individual variables, to examine the individual effects.

Appendix H: Descriptives top 10 EEs

NUTS ID	***D1: Innov Entre***	***H1: Dem***	***H2: Fin***	***H3: Int***	***H4: Kno***	***H5: Lea***	***H6: Fin***	***H7: Net***	***C1: Int-structure***	***C2: Cap***	***C3: EEI***
UKI3-4	8.539	6.028	5.608	14.086	5.657	8.641	5.705	5.725	1.858	1	33.13
NL32	7.116	5.002	5.104	6.577	4.539	5.924	5.505	4.612	1.799	1	25.16
EE00	6.642	**1.956**	4.951	4.476	**3.501**	5.128	4.370	4.403	1.344	1	**7.96**
NL23	6.517	5.002	4.652	4.776	**3.697**	**3.450**	4.435	4.612	1.762	0	14.78
NL31	6.503	5.261	5.278	5.167	4.067	6.723	5.441	4.612	1.780	0	25.18
NL33	6.377	5.121	4.809	5.538	5.142	5.770	5.124	4.612	1.771	0	21.43
DE30	6.359	4.915	4.281	6.846	4.466	4.725	6.361	4.041	1.637	1	20.89
SE11	6.234	4.613	5.916	6.720	8.917	5.610	5.939	4.059	1.792	1	29.08
NL11	6.172	4.030	4.771	4.443	**3.802**	6.278	4.703	4.612	1.667	0	17.52
NL21	6.154	4.526	4.667	4.158	4.000	4.439	4.890	4.612	1.715	0	13.86

** The bold marked values are below the mean of the overall dataset*

Appendix I: Average, summed, minimum lagged models

Average lagged spatial models

	Dependent variable: Innovative Entrepreneurship							
	Independent variables							
	Control model	Demand	Talent	Intermediate	Knowledge	Leadership	Finance	Networks
internal_structure	2.079***	2.160***	2.046***	1.393***	2.163***	1.484***	2.046***	1.959***
	(0.169)	(0.209)	(0.291)	(0.159)	(0.196)	(0.159)	(0.291)	(0.229)
Local independent variable		0.399***	0.413***	0.615***	0.251***	0.470***	0.413***	0.013
		(0.107)	(0.104)	(0.042)	(0.056)	(0.045)	(0.104)	(0.125)
Average lagged variable		-0.503***	-0.449***	-0.180**	-0.416***	0.039	-0.449***	0.044
		(0.119)	(0.124)	(0.087)	(0.090)	(0.077)	(0.124)	(0.139)
Constant	1.228***	1.529***	1.406***	0.380	1.759***	-0.012	1.406***	1.161***
	(0.231)	(0.249)	(0.236)	(0.263)	(0.302)	(0.296)	(0.236)	(0.248)
Observations	259	259	259	259	259	259	259	259
Adjusted R^2	0.368	0.405	0.404	0.657	0.431	0.563	0.404	0.364
Residual Std. Error	0.795 (df = 257)	0.771 (df = 255)	0.772 (df = 255)	0.586 (df = 255)	0.754 (df = 255)	0.661 (df = 255)	0.772 (df = 255)	0.797 (df = 255)
F Statistic	150.958*** (df = 1; 257)	59.536*** (df = 3; 255)	59.201*** (df = 3; 255)	165.778*** (df = 3; 255)	66.193*** (df = 3; 255)	111.671*** (df = 3; 255)	59.201*** (df = 3; 255)	50.250*** (df = 3; 255)
Note:								*p<0.1; **p<0.05; ***p<0.01

Multicollinearity issues are revealed in the VIF-tests, with Talent, lag Talent, lag Networks, Networks, and lag Finance all scoring above the accepted threshold of 5. This suggests a higher degree of correlation between these variables, which is likely due to the inclusion of average measurements from neighbouring regions in the models.
The BP-test shows heteroscedasticity in the Intermediate variable, likely leading to biased estimations within this variable model.

Summed lagged spatial models

	Dependent variable: Innovative Entrepreneurship							
	Independent variables							
	Control model	Demand	Talent	Intermediate	Knowledge	Leadership	Finance	Networks
Internal Structure	2.079***	1.720***	1.872***	1.326***	1.899***	1.604***	1.610***	2.041***
	(0.169)	(0.198)	(0.276)	(0.141)	(0.173)	(0.147)	(0.252)	(0.207)
Local independent variable		0.289***	0.195**	0.551***	0.189***	0.431***	0.303***	0.133**
		(0.067)	(0.078)	(0.042)	(0.051)	(0.044)	(0.076)	(0.062)
Sum lagged variable		-0.640***	-0.550***	-0.213***	-0.580***	-0.340***	-0.570***	-0.548***
		(0.086)	(0.091)	(0.075)	(0.082)	(0.081)	(0.082)	(0.090)

Constant	1.228***	2.324***	2.245***	0.618**	2.323***	1.079***	2.219***	2.269***
	(0.231)	(0.268)	(0.280)	(0.287)	(0.302)	(0.317)	(0.261)	(0.288)
Observations	259	259	259	259	259	259	259	259
Adjusted R^2	0.368	0.477	0.459	0.662	0.486	0.591	0.473	0.445
Residual Std. Error	0.795 (df = 257)	0.723 (df = 255)	0.735 (df = 255)	0.581 (df = 255)	0.717 (df = 255)	0.640 (df = 255)	0.726 (df = 255)	0.745 (df = 255)
F Statistic	150.958*** (df = 1; 257)	79.406*** (df = 3; 255)	74.026*** (df = 3; 255)	169.465*** (df = 3; 255)	82.269*** (df = 3; 255)	125.118*** (df = 3; 255)	78.312*** (df = 3; 255)	70.080*** (df = 3; 255)
Note:								*p<0.1; **p<0.05; ***p<0.01

Above are the summed lagged spatial models, there are no multicollinearity issues are detected, the Intermediate and Network models demonstrate heteroscedasticity.

Minimum lagged spatial models

	Dependent variable: Innovative Entrepreneurship							
	Independent variables							
	Control model	Demand	Talent	Intermediate	Knowledge	Leadership	Finance	Networks
internal structure	2.079***	2.028***	1.465***	1.216***	1.909***	1.510***	1.672***	1.858***
	(0.169)	(0.214)	(0.291)	(0.155)	(0.195)	(0.151)	(0.311)	(0.232)
Local independent variable		0.043	0.268**	0.586***	0.201***	0.474***	0.175*	-0.069
		(0.100)	(0.116)	(0.045)	(0.060)	(0.046)	(0.094)	(0.096)
Minimum lagged variable		-0.022	-0.049	0.022	-0.303	0.006	-0.026	0.162
		(0.100)	(0.110)	(0.114)	(0.185)	(0.106)	(0.105)	(0.100)
Constant	1.228***	1.202***	1.156***	-0.039	1.735***	0.072	1.160***	1.210***
	(0.231)	(0.245)	(0.230)	(0.297)	(0.557)	(0.374)	(0.232)	(0.241)
Observations	259	259	259	259	259	259	259	259
Adjusted R^2	0.368	0.363	0.382	0.651	0.390	0.562	0.373	0.370
Residual Std. Error	0.795 (df = 257)	0.798 (df = 255)	0.786 (df = 255)	0.590 (df = 255)	0.781 (df = 255)	0.662 (df = 255)	0.792 (df = 255)	0.793 (df = 255)
F Statistic	150.958*** (df = 1; 257)	50.043*** (df = 3; 255)	54.116*** (df = 3; 255)	161.709*** (df = 3; 255)	56.007*** (df = 3; 255)	111.476*** (df = 3; 255)	52.146*** (df = 3; 255)	51.586*** (df = 3; 255)
Note:								*p<0.1; **p<0.05; ***p<0.01

Model performance

In terms of model performance indicators, the VIF-test results showed that all variables scored below the threshold of 5, indicating minimal multicollinearity, except for the Finance variable (5.64). Moreover, the BP-test indicated heteroskedasticity in the Talent, Intermediate and Finance models.

Appendix J: Capital control models

Capital control models

	Dependent variable: Innovative Entrepreneurship							
	Independent variable:							
	Control model	Demand	Talent	Intermediate	Knowledge	Leadership	Finance	*Networks*
internal_structure	1.961***	2.089***	1.701***	1.547***	1.963***	1.566***	1.899***	1.893***
	(0.148)	(0.184)	(0.255)	(0.146)	(0.173)	(0.150)	(0.243)	(0.194)
Capital	1.239***	1.038***	1.163***	0.341**	1.111***	0.817***	1.078***	1.218***
	(0.137)	(0.156)	(0.146)	(0.145)	(0.141)	(0.133)	(0.144)	(0.140)
Local variable		0.151*	0.162	0.526***	0.121**	0.369***	0.216**	0.086
		(0.086)	(0.099)	(0.050)	(0.050)	(0.045)	(0.084)	(0.084)
Max lagged variable		-0.262***	-0.076	-0.144***	-0.080***	-0.005	-0.233***	-0.067
		(0.090)	(0.087)	(0.030)	(0.031)	(0.033)	(0.078)	(0.086)
Constant	1.247***	1.678***	1.288***	0.454**	1.150***	0.365	1.519***	1.295***
	(0.202)	(0.247)	(0.220)	(0.206)	(0.221)	(0.224)	(0.225)	(0.239)
Observations	259	259	259	259	259	259	259	259
Adjusted R^2	0.518	0.531	0.520	0.683	0.534	0.618	0.533	0.517
Residual Std. Error	0.694 (df = 256)	0.685 (df = 254)	0.693 (df = 254)	0.563 (df = 254)	0.683 (df = 254)	0.618 (df = 254)	0.683 (df = 254)	0.695 (df = 254)
F Statistic	139.828*** (df = 2; 256)	74.133*** (df = 4; 254)	70.804*** (df = 4; 254)	139.880*** (df = 4; 254)	74.816*** (df = 4; 254)	105.408*** (df = 4; 254)	74.674*** (df = 4; 254)	69.915*** (df = 4; 254)
Note:								*p<0.1; **p<0.05; ***p<0.01

Model performance

In terms of model performance indicators, multicollinearity was identified in Talent, while the BP-tests detected heteroscedasticity in Demand, Talent, Knowledge, Leadership, Finance and Networks.

Appendix K: Excluding single neighbour regions models

Excluding single neighbour regions

	Dependent variable: Innovative Entrepreneurship							
	Independent variables							
	Control model	Demand	Talent	Intermediate	Knowledge	Leadership	Finance	Networks
Internal Structure	2.073***	2.239***	1.655***	1.496***	2.065***	1.553***	1.853***	1.931***
	(0.171)	(0.250)	(0.289)	(0.156)	(0.197)	(0.159)	(0.288)	(0.228)
Local independent variable		0.279***	0.215*	0.582***	0.182***	0.506***	0.298***	0.069
		(0.099)	(0.115)	(0.047)	(0.060)	(0.049)	(0.102)	(0.099)
Max lagged variable		-0.423***	-0.061	-0.128***	-0.100***	0.023	-0.253**	-0.007
		(0.112)	(0.102)	(0.032)	(0.034)	(0.036)	(0.098)	(0.103)
Constant	1.149***	1.761***	1.129***	0.252	0.914***	-0.252	1.393***	1.094***
	(0.232)	(0.288)	(0.255)	(0.206)	(0.256)	(0.244)	(0.263)	(0.276)
Observations	224	224	224	224	224	224	224	224
Adjusted R^2	0.395	0.427	0.401	0.645	0.428	0.592	0.416	0.392
Residual Std. Error	0.752 (df = 222)	0.732 (df = 220)	0.748 (df = 220)	0.576 (df = 220)	0.731 (df = 220)	0.617 (df = 220)	0.739 (df = 220)	0.754 (df = 220)
F Statistic	146.788*** (df = 1; 222)	56.504*** (df = 3; 220)	50.758*** (df = 3; 220)	135.911*** (df = 3; 220)	56.613*** (df = 3; 220)	108.960*** (df = 3; 220)	53.943*** (df = 3; 220)	49.018*** (df = 3; 220)
Note:								*p<0.1; **p<0.05; ***p<0.01

Model performance

Although the exclusion introduced no multicollinearity issues, it flagged heteroscedasticity in the models of Demand, Talent, Intermediaries, and Finance.

Appendix L: Interaction effect models

Interaction effect models

	Dependent variable: Innovative Entrepreneurship							
	Independent variable:							
	Control Model	Demand	Talent	Intermediate	Knowledge	Leadership	Finance	Networks
Internal Structure	2.079***	2.145***	1.547***	1.354***	2.026***	1.454***	2.010***	1.981***
	(0.169)	(0.207)	(0.285)	(0.142)	(0.199)	(0.169)	(0.274)	(0.229)
Local independent variable		0.494**	0.591**	1.130***	0.348	0.738***	0.619***	0.330
		(0.196)	(0.239)	(0.153)	(0.213)	(0.164)	(0.208)	(0.309)
Max lagged variable		-0.472***	-0.160	0.393***	-0.012	0.198	-0.245	-0.107
		(0.176)	(0.179)	(0.151)	(0.180)	(0.136)	(0.171)	(0.219)
Interaction effect local:lagged		-0.021	-0.035	-0.108***	-0.029	-0.052*	-0.056	-0.027
		(0.042)	(0.044)	(0.030)	(0.041)	(0.031)	(0.047)	(0.057)
Constant	1.228***	1.686**	0.907	-2.116***	0.516	-0.835	0.965	1.007
	(0.231)	(0.731)	(0.722)	(0.696)	(0.827)	(0.631)	(0.686)	(0.959)
Observations	259	259	259	259	259	259	259	259
Adjusted R^2	0.368	0.450	0.402	0.691	0.421	0.566	0.434	0.373
Residual Std. Error	0.795 (df = 257)	0.742 (df = 254)	0.773 (df = 254)	0.555 (df = 254)	0.761 (df = 254)	0.659 (df = 254)	0.752 (df = 254)	0.792 (df = 254)
F Statistic	150.958*** (df = 1; 257)	53.709*** (df = 4; 254)	44.316*** (df = 4; 254)	145.563*** (df = 4; 254)	47.812*** (df = 4; 254)	85.072*** (df = 4; 254)	50.457*** (df = 4; 254)	39.326*** (df = 4; 254)
Note:								*p<0.1; **p<0.05; ***p<0.01

Model performance
Looking at the performance indicators, multicollinearity is expected as one variable, the interaction effect, is made up of two other predictors. Therefore, the multicollinearity might mess with some of the sizes of the coefficients. However, if significant effects occur the presence is more important than the size. Checking for heteroscedasticity showed that Demand and Finance have significant heteroskedasticity, which may invalidate the models. All other models show homoscedasticity.

Appendix M: Better neighbour dummy models

Better neighbour dummy models

	Dependent variable: Innovative Entrepreneurship							
	Independent variables:							
	Control model	Demand	Talent	Intermediate	Knowledge	Leadership	Finance	Networks
Internal Structure	2.079***	2.083***	1.507***	1.291***	1.899***	1.569***	1.669***	2.007***
	(0.169)	(0.201)	(0.281)	(0.139)	(0.180)	(0.151)	(0.269)	(0.209)
Local independent variable		-0.099	0.169**	0.519***	0.044	0.399***	0.094	-0.079
		(0.063)	(0.085)	(0.048)	(0.058)	(0.054)	(0.081)	(0.065)
Neighbour dummy		-0.767***	-0.337***	-0.295***	-0.642***	-0.293**	-0.400***	-0.647***
		(0.133)	(0.114)	(0.109)	(0.127)	(0.126)	(0.116)	(0.115)
Constant	1.228***	2.249***	1.560***	0.440*	1.803***	0.544*	1.691***	2.107***
	(0.231)	(0.293)	(0.264)	(0.248)	(0.296)	(0.292)	(0.274)	(0.282)
Observations	259	259	259	259	259	259	259	259
Adjusted R^2	0.368	0.437	0.402	0.661	0.440	0.571	0.401	0.434
Residual Std. Error	0.795 (df = 257)	0.750 (df = 255)	0.773 (df = 255)	0.582 (df = 255)	0.749 (df = 255)	0.655 (df = 255)	0.774 (df = 255)	0.752 (df = 255)
F Statistic	150.958*** (df = 1; 257)	67.722*** (df = 3; 255)	58.796*** (df = 3; 255)	168.713*** (df = 3; 255)	68.457*** (df = 3; 255)	115.653*** (df = 3; 255)	58.532*** (df = 3; 255)	66.939*** (df = 3; 255)
Note:								*p<0.1; **p<0.05; ***p<0.01

Model performance
The VIF scores were within acceptable limits, indicating no multicollinearity issues. However, the BP-test showed significant heteroscedasticity for the Demand, Talent, and Finance models.