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The European Deep Tech Landscape
A Comparative Analysis of Innovation Ecosystems and Venture Density

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Abstract

In recent years, the European Union has come to identify the need to close the innovation gap with the other global leaders. One of its key strategies is to invest in European-based technology within high-potential sectors such as Deep Technology. The factors that drive the clustering of deep tech ventures across different regions, however, are not yet fully understood by research. Moreover, there are limited studies regarding the effectiveness of place-based policies such as the Regional Innovation Valley (RIV) initiative. This thesis uses a quantitative cross-sectional approach across 217 European regions to examine the extent to which Human, Financial, and Network regional capabilities predict Deep Tech venture presence, and whether the RIV designation influences these relationships. The findings suggest a hierarchy among regional capabilities. Human capital is the primary driver, consistently linked to higher venture density. Network Capability serves as a flexible tool to enhance regional efficiency, while the Financial Capability has no significant effect on the presence of deep tech ventures. The moderation analysis suggests that the RIV designation signals network capabilities, strengthening the link between connectivity and venture density, especially in developing ecosystems. This implies that such policies can foster regional cohesion rather than just rewarding established hubs. However, the findings also caution stakeholders against prioritizing connectivity in regions lacking sufficient talent, as human capital remains the foundational driver.

Keywords: Deep Tech, Innovation Ecosystems, European Regions

Contents

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Chapter 1

Introduction

1.1 Background and Problem Description

The European Union (EU) is currently grappling with the monumental challenge of how to close the persistent innovation gap with other global leaders like the United States and China, and at the same time foster the ability to scale up new technologies (Draghi, 2024). At the heart of this issue is the pressing need to support and grow a new wave of Europe-based Tech giants. This is a complex process that involves finding more effective ways to bring fundamental scientific breakthroughs to market, which is where deep technology plays a critical role. Unlike incremental improvements, deep tech is grounded in major scientific advances (Basilio Ruiz De Apodaca et al., 2022). Its development is crucial not just for maintaining the EU's economic independence, but also for tackling major societal issues such as the energy transition and public health (European Commission, 2025).

Turning these scientific breakthroughs into successful businesses, however, is inherently complex. Deep tech startups, in particular, encounter a distinct set of hurdles. They often require long development timelines, must navigate complex integration with existing industries, and face the so-called "valley of death", the initial period when research funding is essential but commercial revenues are not yet in sight. Overcoming this gap demands large amounts of patient capital and access to advanced infrastructure (Romme et al., 2023; Grande et al., 2025; Frank et al., 1996). Moreover, whether these knowledge-intensive firms succeed or fail often comes down to where they are located. Regional factors like the availability of specialized talent, cutting-edge facilities, and strong collaborative networks play a decisive role (Audretsch and Lehmann, 2005; Kowal and Przewoźnik, 2025). For many deep tech founders, these local disparities can determine the viability of building a viable company. Consequently, policies designed to promote deep tech development should be formulated and implemented at the level of regional entrepreneurial ecosystems (Stam, 2015).

1.2 Situating the Research and Context

One of the most effective ways to understand the challenge of building regional innovation capacity is to use the innovation ecosystem perspective. This approach views innovation as something that emerges from the interactions between different actors, resources, and institutions, all of which are shaped by the specific context of a region (Granstrand and Holgersson, 2019; Stam, 2015). This study employs a framework that decomposes the ecosystem into three core capabilities that are believed to be pivotal for deep tech development (Stam, 2018; Szopik-Depczyńska et al., 2020).

Human & Knowledge Capability (H) captures the regional stock of specialized expertise, highly skilled labour, and the knowledge output of universities and Research and Technology Organisations (RTOs) (Audretsch and Lehmann, 2005). Financial & Infrastructure Capability (F) describes the ability of the region to support the ventures in targeting the key resource deficit identified by Romme et al. (2023) and Grande et al. (2025). Deep tech ventures depend on patient, risk-accepting finance to traverse the 'valley of death, and this dimension approximates the structural presence of such resources by tracking the broader regional investment base, including corporate R&D stocks and advanced physical infrastructure. Finally, Network & Collaboration Capability (N) captures the intensity of institutional interconnections and the co-creation capacity required to align the activities of science, industry, and government (Audretsch et al., 2022).

In recent years, the EU has intensified efforts to strengthen these capabilities, largely in response to a new political rationale for intervention shaped by the "urgency of the innovation gap" articulated in the Draghi Report. Draghi's assessment recast the shortage of scale-ups not merely as a market failure, but as a source of geopolitical risk. Emphasizing that Europe has not produced a single firm founded from scratch and reaching a valuation above 100 billion euros in the last fifty years, the report persuasively argued that Europe's "static industrial structure" risks a trajectory of "slow agony" (Draghi, 2024).

One of the main policy measures introduced by the EU to address these challenges is the Regional Innovation Valleys (RIV) initiative, as part of the New European Innovation Agenda (European Commission, 2025). The RIV initiative is intended to help reduce the innovation gap and encourage cooperation between regional deep tech ecosystems. It does so by promoting cross-regional alliances and supporting greater alignment of Research and Innovation (R&I) strategies (Kelchtermans et al., 2025). The RIV label is theorized to serves as both a coordination mechanism and a signal to raise the visibility of participating regions, making it easier to mobilise and combine existing capabilities more effectively (Roundy and Fayard, 2018).

1.3 Research Gaps and Contribution

While there has been substantial theoretical discussion around the Knowledge Spillover Theory of Entrepreneurship (KSTE), as well as frequent application of the ecosystem framework in empirical research, there is still limited understanding of how deep tech ventures form in the European context (Acs et al., 2009; Hu et al., 2024). A review of the existing literature highlights three ongoing debates that this thesis will explore.

The first debate concerns the idea of 'Entrepreneurial Spawning', or how new ventures emerge from established firms. Much of the theory in this area is based on studies from the United States, which suggest that regions with many large, R&D-focused companies tend to generate more spin-offs. According to this view, employees gain valuable experience in these firms and go on to start their own businesses (Gompers et al., 2005; Klepper, 2001). Because of this, one could look at the level of corporate R&D as a sign of how many new startups might appear. However, recent work that focuses specifically on Europe suggests the story may be different here. The Draghi report in fact, suggests that European industries can be more rigid than those in the US (Draghi, 2024). In these cases, large companies tend to retain resources rather than letting them flow to new businesses, which may limit the kind of 'spillover' effect that theory predicts (Choi and Phan, 2006). So far, there is not much clear evidence on whether corporate innovation in Europe actually leads to more deep tech startups, or if these resources get stuck within established firms instead.

A second debate is whether the knowledge spillover theory applies in the same way to sectors with more barriers to entry, like deep tech. Many studies group all 'knowledge-intensive firms' together and often focus on industries such as ICT or advanced manufacturing (Audretsch and Lehmann, 2005; Baptista and Mendonça, 2010). These studies tend to assume that, as long as a region has enough skilled people and research facilities, knowledge will naturally spill over and lead to new startups. However, deep tech companies often face very different challenges. They usually need more capital up front, take longer to develop their products, and rely on support from specialized partners (Frank et al., 1996; Grande et al., 2025; Romme et al., 2023). There is still not much research on whether the usual factors like talent and clustering are as important for deep tech, or if other resources matter more in these settings.

A third area of debate is about how resources in innovation ecosystems are measured (O'Connor et al., 2018; Stam, 2018). Regional studies often use broad indicators like the Regional Innovation Index. These indicators mix static elements, such as R&D spending or education levels, with dynamic ones like partnerships and collaboration networks (European Commission et al., 2025; Schibany and Streicher, 2008). While recent theories suggest that these dynamic factors are crucial, most studies still treat all of these resources as if they have the same impact (Roundy and Fayard, 2018). Because of this, it is still unclear which resources are essential building blocks and which ones actually help new ventures get off the ground (Leendertse et al., 2022). More precise ways of measuring resources could make it easier to understand their real effects.

Addressing these gaps could have real practical benefits. Policymakers might be able to design better programs that stop resources from going unused. Investors could gain a clearer picture of how the local context and networks help new companies succeed, which could help them decide where to put their capital, and entrepreneurs might gain insight into high-potential regions in Europe. Finally, the findings from this research could feed into place-based policies, like the Regional Innovation Valley initiative, and make sure that public funds actually help the deep tech sector grow.

1.4 Research Question and Thesis Outline

This study looks at what factors help explain how many deep tech startups exist in different regions, using quantitative data to back up the findings. It also considers how certain policy interventions might make a difference. The research question is set out in the conceptual framework, which helps clarify the main relationships being studied. (Figure 2.1):

textitHow do regional innovation ecosystem capabilities explain the regional variation in the density of active deep tech ventures, and how does the Regional Innovation Valley designation moderate these relationships?

The conceptual framework for this study uses data from the European Regional Innovation Scoreboard to define three key capability areas, labelled H, F, and N. To analyze the data, Multiple Linear Regression (MLR) models are used, including a version that applies a log transformation. The analysis draws on information from 217 European regions and nearly 7,000 ventures, and examines whether the RIV initiative changes how these factors relate to each other.

The structure of the thesis is as follows. Chapter 2 covers the main literature, defines key terms, and sets up the theoretical background, ending with a statement of the main hypotheses (H1 to H6). Chapter 3 explains the methods used, including how the data was processed, how variables were built, and how any unusual data points were handled. Chapter 4 goes through the results analysis, comparing the linear and log-transformed versions of the models. Finally, Chapter 5 discusses what the findings mean more broadly, connects them back to the theory, gives suggestions for the stakeholders, notes limitations of the study, and suggests venues of future research.

Chapter 2

Literature Review

2.1 Deep Tech: Definition and Unique Ecosystem Dependencies

Looking at the current innovation landscape, deep tech stands out from more traditional tech advances because it is based on major scientific or engineering breakthroughs, rather than incremental improvements (Basilio Ruiz De Apodaca et al., 2022). Digital innovation is often linked to software startups that grow quickly by using existing platforms. Deep tech companies, on the other hand, usually build their business models around their own research and development (Basilio Ruiz De Apodaca et al., 2022; Tutida et al., 2022).

A good example of this is CRISPR technology. Showing not only how deep tech can bring about major changes, but also highlighting the higher risks that come with breakthroughs in this field. As it enables precise gene editing and creates new opportunities in medicine and agriculture, it also exemplifies the substantial R&D investments required, having taken decades to develop (Dalgan and Wei, 2025; Gostimskaya, 2022). This strong reliance on breakthroughs suggests that deep tech business models deserve special academic attention, to avoid being grouped with the more step-by-step improvements seen in 'shallow-tech' innovation.

Looking more closely, deep tech faces three main challenges. First, moving discoveries from the lab to the market takes a long time and involves significant risk. As a result, these companies often go years without making a profit, stuck in the gap between proving a concept works and actually selling a product. Second, deep tech products usually need to combine specialised hardware, software, and electronics, which makes development even more complex. Third, because the R&D process is long and the products are often physical, startups in this field have to raise a lot of capital just to prototype, test, and launch their ideas (Grande et al., 2025; Romme et al., 2023).

Because of these challenges, deep tech companies often depend heavily on outside resources and support. Dealing with so much uncertainty means they need access to specialised talent and knowledge, which usually comes from universities or public research organisations (Grande et al., 2025; Nguyen et al., 2024). On top of this, their long development cycles mean they need investors who are willing to wait and take bigger risks (Briggs, 2025; Nguyen et al., 2024). These startups also rely on advanced labs and testing facilities, and to actually get their products to market, they need strong networks that connect universities, industry, investors, and the government, especially when regulations are involved (Grande et al., 2025). Altogether, these points hint at just how much deep tech ventures rely on their external environment to succeed.

These kinds of dependencies are often shaped by local conditions (Tödtling and Trippl, 2005; Sternberg, 2022). For example, life sciences clusters in cities like Cambridge or Paris would depend on close ties between research hospitals, universities, and biotech firms (Baptista and Mendonça, 2010; Reichert, 2019). In the case of semiconductor hubs such as Dresden, shared access to advanced manufacturing facilities is key (Grande et al., 2025).

Complex, knowledge-intensive activities are typically concentrated in specific areas due to the proximity of essential resources and critical expertise is most effectively transferred through direct, in-person interactions (Andersson, 2005; Kuah, 2002). New companies often do better when they are located near other businesses, universities, and institutions, as being close helps ideas spread and supports growth (Hu et al., 2024; Kuah, 2002; McCann and Van Oort, 2019). In theh context of deep tech companies, depending on local networks to find talent and expertise shows just how important the regional setting is.

Because of this, it mkaes little sense to study deep tech companies without looking at their local context, as these firms rely on access to important resources that can vary a lot from one region to another (Kowal and Przewoźnik, 2025). The fact that deep tech ventures are so closely linked to their local ecosystems made up of different people, resources, and organisations, means that these networks can have a major impact on whether new businesses succeed. To really understand what helps deep tech grow, it is important to use methods that measure and compare the local innovation environment. This way, it becomes possible to spot the strengths, weaknesses, and dynamics in each region that help explain why deep tech companies take root there.

2.2 The Innovation Ecosystem Perspective

Given all this, the innovation ecosystem framework offers a modern way to look at how innovation works in real-world settings, especially those that are complex and interconnected. Instead of just focusing on single companies or markets, this approach considers all the people, activities, technologies, and institutions involved (Granstrand and Holgersson, 2019; Pidorycheva et al., 2020). An innovation ecosystem brings together a range of actors, such as companies, universities, research centres, governments, suppliers, and even competitors. These groups create new value by sharing knowledge, and this process depends a lot on how local institutions and learning systems work (Audretsch et al., 2022; Granstrand and Holgersson, 2019; Audretsch and Belitski, 2017; Fischer et al., 2018).

This way of thinking moves the spotlight beyond just firms or industries (Pidorycheva et al., 2020). Unlike the older Innovation Systems (IS) model, which mainly looked at big-picture policies, the ecosystem approach pays more attention to the actions of entrepreneurs and how different players depend on each other (Santos, 2024; Stam, 2015). It also focuses on both the technologies and resources involved and looks at both teamwork and rivalry between actors (Granstrand and Holgersson, 2019; Santos, 2024).

One of the strengths of the ecosystem perspective is that it makes it possible to measure things like local talent, funding, and infrastructure, as well as spot any key challenges (Audretsch et al., 2022; O'Connor et al., 2018). This information is crucial for creating better policies to boost innovation and for helping entrepreneurs figure out the best places to start or grow their companies (Guzman et al., 2023; Sternberg, 2022). The ecosystem approach also helps compare regions and see what each one does well, which might be especially important for deep tech firms (Stam, 2018; O'Connor et al., 2018).

Even though the innovation ecosystem framework seems well-suited for studying how deep tech depends on its local environment, the research using this approach is still at an early stage and faces some major hurdles. For example, there is not much work on how geography shapes knowledge-intensive entrepreneurship, and the impact of deep tech spin-offs is still not fully understood (Audretsch and Lehmann, 2005; Grande et al., 2025). Studies that look closely at how high-tech startups develop and how their ecosystems form are also quite rare (Cuvero et al., 2022). On top of that, researchers have often missed how important it is for different ecosystem players to share knowledge, which is key for creating complex new innovations (Audretsch et al., 2022). Another challenge is that there are not many reliable and comparable ways to measure how these ecosystems work, most studies use either case studies or broad indicators that might oversimplify (Leendertse et al., 2022; Szopik-Depczyńska et al., 2020; Teirlinck and Spithoven, 2023). Because of these gaps, there is a real need for more detailed, data-driven methods that can pinpoint exactly which ecosystem features help deep tech clusters thrive.

2.3 Measuring Ecosystems

When it comes to measuring how different regions in the EU perform in innovation, the Regional Innovation Scoreboard (RIS) is the main tool used by the European Commission (European Commission, 2025). The RIS builds on the country-level European Innovation Scoreboard (EIS), but focuses on regions instead. It uses the NUTS classification system, which splits the EU into three levels: NUTS 1 covers large socio-economic regions, NUTS

2 is for smaller areas used in regional policy, and NUTS 3 breaks things down even further for more detailed analysis. Using this system makes it easier to compare regions in a consistent way (European Commission et al., 2025; Lanzetta and Ponsiglione, 2024). This is important because innovation systems can be very different from one region to another (Hajek and Henriques, 2017; Szopik-Depczyńska et al., 2020).

Looking at how the RIS works, it measures regional innovation using a composite indicator called the Regional Innovation Index (RII). This index is built around four main pillars that reflect different stages of the innovation process (European Commission, 2025). First, 'Framework Conditions' look at basic inputs like skilled workers, international links, and digital infrastructure. Second, 'Investments' keep track of capital going into R&D from both public and private sources. Third, 'Innovation Activities' track how companies turn these investments into real outputs, like SME innovation and new patents. Finally, 'Impacts' measure the bigger effects on jobs, sales, and the environment (European Commission et al., 2025). This set-up captures how innovation is shaped by a multitude different factors and lines up well with ecosystem theory, which says results come from the way different people and organisations interact (Leendertse et al., 2022; Szopik-Depczyńska et al., 2020; Tödtling and Trippl, 2005).

The RIS dataset that allows to track and compare how regions in Europe innovate over time (European Commission, 2025; Schibany and Streicher, 2008). Because of its reliability, academics often use RIS data to measure and analyze regional innovation (Banga and Gaile-Sarkane, 2025; Lanzetta and Ponsiglione, 2024). It's also used to group similar regions together and to help build tools that can predict policy outcomes (Hajek and Henriques, 2017; Szopik-Depczyńska et al., 2020).

Even though the RIS is useful, it does have some important limitations, especially when trying to study deep tech ecosystems. One issue is that it mostly focuses on input metrics and uses averages that might hide major differences between regions. This is a problem because deep tech relies so much on specific local resources and tends to be very location-based (Teirlinck and Spithoven, 2023; Schibany and Streicher, 2008; Szopik-Depczyńska et al., 2020). Since deep tech companies need special infrastructure, talent, and strong local networks, the overall scores from the RIS might not fully show what really matters for these firms (Iking, 2009; Szopik-Depczyńska et al., 2020; Teirlinck and Spithoven, 2023). To get around this, this study starts with the RII but breaks down its data into more specific parts, which makes it easier to see which ecosystem factors are most important for supporting deep tech (Iking, 2009).

2.4 The Strategic Role of EU Policy

When looking at public policy in the EU, it is clear that the approach has changed over time. In the past, regulations mostly focused on keeping large companies in check, but now there is a bigger effort to help new businesses get started and to support entrepreneurship (Gilbert et al., 2004). This change comes from the realisation that Europe's economic edge is less about traditional aspects like capital and labour, and more about knowledge and innovation. As a result, entrepreneurship is now seen as a key way to drive both economic growth and community development (Audretsch and Lehmann, 2005; Baumol and Strom, 2007; Gilbert et al., 2004). Today, policy tools are used to actively shape innovation ecosystems and set up the basic conditions needed for new businesses to thrive (Stam, 2015, 2018).

A good example of this new approach is the Regional Innovation Valleys (RIV) initiative, which is a major project in the New European Innovation Agenda. The main aim of the RIV is to unlock Europe's innovation potential by finding, connecting, and building up regional innovation ecosystems, with the goal of closing the gap between regions. It fosters collaboration between more and less innovative regions to create cross-regional synergies and accelerate the development and deployment of deep tech and other innovations. Additionally, participating valleys commit to coordinating their R&I policies around key EU strategic priorities, leveraging complementary smart specialisation strategies of the involved regions (European Union, 2025; Kelchtermans et al., 2025).

It is evident that the RIV initiative directly targets the augmentation of ecosystem capabilities vital for sustaining productive entrepreneurship. Since innovation stems from knowledge-based activities, highly skilled workers and R&I investment are critical inputs (Qian et al., 2012; Stam, 2015). Therefore, RIV participation requires regions to enhance the coordination and align the direction of R&I policies, connecting academic excellence across borders to mobilise tacit knowledge and improve regional sensing capacities (European Union, 2025; Kelchtermans et al., 2025; Roundy and Fayard, 2018). Moreover, the initiative also commits significant co-funded capital (over €116 million to start) and leverages shared infrastructure, such as deep-tech hubs and testbeds, mobilising the region's financial and infrastructure resources (European Union, 2025; Kelchtermans et al., 2025). Access to such finance and facilities is crucial for innovative projects characterised by long time horizons and high uncertainty (Stam, 2018; Kerr and Nanda, 2008). Finally, the RIV framework requires strategic, multi-regional partnerships between innovation leader regions and emerging innovators to create cross-regional knowledge exchange and accelerate technology diffusion (Kelchtermans et al., 2025).

The RIV designation does more than just provide resources, as it also plays an important role in helping regions work together and sending clear signals about their strengths (Kelchtermans et al., 2025). When policy is done well, it can guide how groups act and help shape the direction of the economy (Feldman and Lowe, 2018). In theory, the RIV label is also meant to boost a region's visibility and reputation across European innovation networks, making it easier for them to stand out. By doing so, it signals the quality of its entrepreneurial environment to external actors such as investors and partners, thereby reducing information asymmetries about the regional entrepreneurial environment (Kelchtermans et al., 2025; Roundy and Fayard, 2018). Some researchers argue that having a designation, like RIV, could actually help regions make better use of their resources. By making resources more visible and easier to connect, the RIV label might strengthen the link between what a region has to offer and the success of new businesses (Li et al., 2023; Roundy and Fayard, 2018).

2.5 Three Ecosystem Dimensions for Deep Tech

To fill the gaps found in the literature, this study builds a conceptual framework based on the idea that an ecosystem is made up of different, unique capabilities. Fundamentally, it proposes that deep tech presence is a function of specific regional capabilities. Drawing on the ecosystem perspective, this study introduces a model (Figure 2.1) that disaggregates the RIS data into three core dimensions: Human & Knowledge, Financial & Infrastructure, and Network & Collaboration. This approach aims at proposing a novel, quantitative contribution to a domain where studies have been limited and metrics scarce (Cuvero et al., 2022; Leendertse et al., 2022), allowing for a direct test of which ecosystem capabilities are most critical for translating regional potential into deep tech innovation outcomes.

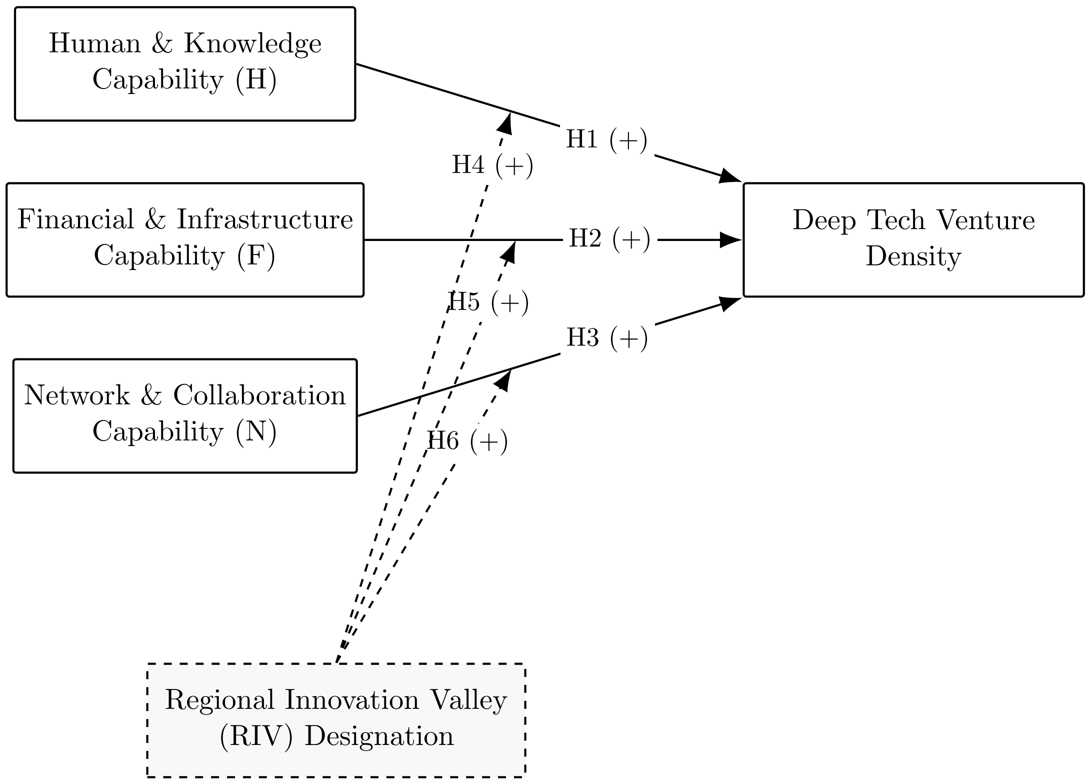


Figure 2.1: Conceptual Model: The Impact of Regional Ecosystem Dimensions on Deep Tech Venture Density, Moderated by RIV Designation.

Figure 2.1 presents the conceptual model employed in this study. In constructing this model, the dependent variable is defined as Deep Tech Venture Density, the number of deep tech startups per million inhabitants in an European (NUTS1/2) region. This operationalisation is directly motivated by the literature, which establishes deep tech venture formation and retention as a critical, yet geographically uneven, driver of innovation (Grande et al., 2025; Romme, 2022; Romme et al., 2023). Furthermore, the decision to normalise by population size, resulting in a per-million measure, facilitates inter-regional comparability by adjusting for differences in population size and enables more accurate assessments of regional performance.

Deep tech ventures play an important role in supporting Europe's economic independence, competitiveness, and future growth (Grande et al., 2025; Draghi, 2024). These ventures stand out because they have the potential to create entirely new markets, change the way technologies are used, and offer crucial tools for big changes in society (Grande et al., 2025; Kowal and Przewoźnik, 2025). Being able to turn new inventions into successful businesses is seen as a key way to tackle major challenges and address some of the long-standing weaknesses in Europe's innovation system (Romme et al., 2023).

When looking at the theoretical and empirical evidence, the geographic concentration of such knowledge-intensive entrepreneurship presents a central puzzle. On one hand, the Knowledge Spillover Theory of Entrepreneurship (KSTE) posits that entrepreneurial activity will be spatially localised within close geographic proximity to the knowledge source (Audretsch and Lehmann, 2005). Looking at the valley of death for deep tech, it becomes clear that turning knowledge into a business is a real challenge, and it doesn't happen everywhere. The fact that some regions might be better at building and growing deep tech companies highlights just how much local ecosystem factors matter.

Because of this, Deep Tech Venture Density is used as the main outcome variable for the study. It shows how well a region is able to overcome the big hurdles of deep tech and turn its resources into real economic results. By looking at what drives this density, the study aims to fill the gap in understanding why some regions are more successful at fostering high-impact entrepreneurship than others (Audretsch and Lehmann, 2005; Grande et al., 2025).

To explain these differences, the model looks at three main independent variables: Human & Knowledge Capability (H), Financial & Infrastructure Capability (F), and Network & Collaboration Capability (N). Each of these is built from specific groups of indicators taken from the RIS data, to endure the measures are consistent and reliable across regions (European Commission et al., 2025).

The model also includes the RIV designation as a moderating factor, which might boost how well these resources work together. Research suggests that coordinated policies like the RIV can make regional resources more effective by improving visibility, connectivity, and planning (Kelchtermans et al., 2025; Roundy and Fayard, 2018). In this study's model, this effect is shown with dashed arrows, meaning that the impact of each resource could change depending on whether a region has RIV status.

2.5.1 Hypothesis 1: Human & Knowledge Capability

The first hypothesis suggests that regions with stronger human capital and more knowledge-generation are likely to have more deep tech startups. This idea is based on theory that shows a strong link between knowledge resources and entrepreneurial success.

When looking at the theoretical mechanisms, the KSTE frames entrepreneurship as an endogenous response to the potential for commercialising knowledge that incumbents have not adequately exploited (Audretsch and Lehmann, 2005). The theory suggests that the presence of knowledge capacity in a region positively influences the number of firms located close to the knowledge source, with the mobility of highly educated human capital serving as a key channel for these spillovers (Audretsch and Lehmann, 2005). This mechanism is particularly important for independent new ventures. Research also confirms that localisation economies, and the knowledge spillovers they generate, are particularly important for independent start-ups (Bosma et al., 2007). Furthermore, studies explicitly analyzing the impact of regional factors find that local access to a university, students, and graduates significantly influences the entry of knowledge-based firms, particularly in knowledge-intensive service sectors and high-tech manufacturing, where specific human capital is key (Baptista and Mendonça, 2010). Consequently, this is expected to translate into a positive, highly significant general effect of human capital on entrepreneurship, also termed entrepreneurial absorptive capacity (Qian et al., 2012).

For deep tech specifically, this link is theorised to be not just positive but fundamental. Deep tech ventures are built on major breakthroughs in science and engineering (Grande et al., 2025). To develop these kinds of companies, teams need to go through complicated research processes that often involve many different academic fields. As a result, deep tech ventures seem to have a heightened need for highly qualified individuals with specialised, advanced training to address significant technological uncertainty and overcome the valley of death (Grande et al., 2025; Romme et al., 2023). Regions hosting RTOs, or institutions focused on applied research and technological development, as well as leading universities, provide the world-class infrastructure and expert knowledge necessary convert research achievements into market-ready innovations. These institutions commonly serve as the origin points for core technologies used by deep tech ventures (Grande et al., 2025).

Consequently, it seems reasonable to theorise that the availability of specialised human capital and advanced knowledge outputs within a region is a critical, non-substitutable driver of deep tech formation. The model formalises this expectation in the following hypothesis:

$\mathbf{H_1}$: The Human & Knowledge Dimension is positively associated with deep tech venture density.

2.5.2 Hypothesis 2: Financial & Infrastructure Capability

Regarding the second hypothesis, it is proposed that regions with greater financial depth and advanced, specialised infrastructure will foster higher deep-tech venture density. This idea points to just how important resources are when trying to innovate in situations that are risky and uncertain.

Recent research on entrepreneurship often points out that getting access to capital is a major factor in starting and growing a business (Leendertse et al., 2022). This is especially important for new projects that are risky and take a long time to pay off, since these ventures need patient investors who understand the field (Kerr and Nanda, 2008). Along the same lines, having strong physical infrastructure like good facilities and transportation is seen as essential for supporting entrepreneurship (Audretsch et al., 2015).

For deep tech, these needs are even more important. Deep tech startups usually need a lot more capital up front and have longer development periods than typical digital tech companies (Grande et al., 2025). It can take five to seven years for these firms to bring a product to market, which means they face big financial hurdles and cash flow problems (Romme et al., 2023). Another thing to consider is that the potential for new ventures often comes from the region's wider industrial base. According to the Knowledge Spillover Theory of Entrepreneurship, new startups can be built on the unused knowledge held by big, established firms in the area (Acs et al., 2009). This means that regions with high R&D spending in related sectors might act like incubators, with large, research-focused companies serving as training grounds where future entrepreneurs gain the skills and knowledge they need before starting their own businesses (Gompers et al., 2005; Klepper, 2001). Thus, a region's financial depth should perhaps not only be a measure of available cash, but a proxy for the 'technological opportunity' generated by corporate investment that fuels new firm formation (Choi and Phan, 2006).

Yet, research demonstrates that while finance is necessary to prevent failure, it might not be sufficient to drive growth, acting more as a threshold condition than a linear scaler (Hall, 2010). Concurrently, deep tech's development depends on access to world-class research and technology infrastructures, which are instrumental in transforming cutting-edge research into market-ready innovations (Grande et al., 2025). The technological risk inherent in this process is reduced by obtaining access to the most advanced technological breakthroughs and specialised expertise within the regional ecosystem (Romme et al., 2023).

Therefore, regions that provide patient, risk-tolerant capital and advanced, sector-specific infrastructure are expected to directly mitigate the core liabilities of deep tech entrepreneurship. They would supply the essential resources to navigate the protracted, capital-intensive path from laboratory discovery to industrial prototype. The model formalizes this expectation in the following hypothesis:

H_2: The Financial & Infrastructure Dimension is positively associated with deep tech venture density.

2.5.3 Hypothesis 3: Network & Collaboration Capability

In developing the third hypothesis, it is proposed that regions with denser innovation networks and stronger collaborative capacity will likely foster greater deep tech venture density. This dimension captures the flow of knowledge that is essential for innovation. Using the metaphor of knowledge spillovers as the fuel for entrepreneurship, the networks and collaborations within an ecosystem can be seen as the pipes and pumps that help distribute and recombine this fuel. This concept is central to the innovation ecosystem perspective, which frames innovation as a co-creative process within networks of interdependent actors (Audretsch et al., 2022).

When looking at how this knowledge actually spreads, it mostly happens through social networks, with being close together in the same region making it easier for ideas to flow (Reichert, 2019). In practice, this means that knowledge-based startups often cluster near the source of new knowledge (Audretsch and Lehmann, 2005). Well-connected networks can help information move more easily, which helps entrepreneurs spot new opportunities (Roundy and Fayard, 2018). Ecosystems that provide things like business planning support, introductions to important partners, and access to expert advice are often seen as key for helping startups succeed (Kondo, 2006).

For deep tech ventures, having strong connections is essential because their innovations depend on working with a multitude different partners, like universities and research labs. Getting these new technologies to market is hard, partly because it is difficult to get scientists, industry, government, and investors to work together (Kowal and Przewoźnik, 2025). Research and Technology Organizations play a key role by helping move discoveries out of the lab and into the real world (Grande et al., 2025). The big risk here is that a deep tech startup might not be able to get all the important partners on board (Romme et al., 2023). Good ecosystems help by making it easier for skilled people to move between organizations, building stronger connections, and creating a supportive culture (Walsh, 2019).

Then, it stands to reason that regions where different groups like universities, industry, investors, and government, are closely connected are better at reducing the risks of collaboration and speeding up the process of getting deep tech innovations to market. These regions could presumably provide the social and institutional support needed to keep knowledge moving and help everything work together smoothly. The model presents this expectation in the following hypothesis:

H_3: The Network & Collaboration Dimension is positively associated with deep tech venture density.

2.5.4 Hypotheses 4-6: The Moderating Role of RIV Policy

For the final set of hypotheses, the expectation is that the RIV designation has a positive effect on the link between each ecosystem dimension and deep tech venture density. This reflects the view that strategic policy acts not just as a source of funding, but as an active force that shapes the environment and workings of innovation ecosystems (Feldman and Lowe, 2018; Stam, 2015).

The RIV initiative is explicitly designed to strengthen innovation ecosystems across the European Union by fostering interregional collaboration (European Union, 2025). Theoretically, it seems to operate through two primary mechanisms that enhance the impact of a region's existing resource base. To begin with, it acts as a powerful coordinating and signaling mechanism. Here, institutional theory suggests the RIV label increases visibility and reputation as an innovative region, thereby reducing information asymmetries for external resource providers, such as investors and talent (Kelchtermans et al., 2025). This use of policy as a signaling mechanism is not exclusive to the EU, for example, successful policies in South Korea, such as the Tech Incubator Program for Startups (TIPS), leverage private venture capital assessment to signal quality and match public funding, enhancing market dynamics (Yim et al., 2024). Second, it directly augments the connective and collaborative capacity of ecosystems by requiring regions to enhance the coordination and directionality of their R&I policy and engage in collaboration between more and less advanced regions (Kelchtermans et al., 2025; European Union, 2025). This seems to align with the broader policy approach of connecting the institutions and infrastructures that determine outcomes (Audretsch et al., 2020). Critically, however, the effectiveness of such interventions depends on the regional context, necessitating a place-based, holistic approach rather than a one-size-fits-all policy (Content et al., 2019; Szerb et al., 2019).

In the context of this thesis, the RIV designation is thought to strengthen the impact of a region's core capabilities. This idea fits with recent research showing that the entrepreneurial ecosystem itself can act as a moderator, affecting how strongly organizational capabilities influence innovation outcomes (Ferreira et al., 2022). The RIV initiative can therefore be seen as a targeted policy effort aimed at improving a particular part of the regional ecosystem. By analogy, it stands to reason that for a region with strong Human & Knowledge capabilities, the label can enhance its visibility, helping to attract and retain the specialized talent deep tech requires (Qian et al., 2012). For a region with strong Financial & Infrastructure capabilities, a coordinated agenda and reputation can improve alignment between patient capital and high-potential ventures. Finally, for a region's Network & Collaboration Capability, the RIV framework provides a formal structure and mandate to deepen and extend inter-regional partnerships, which could result in directly strengthening the connective tissue dimension of ecosystems.

Consequently, the model hypothesizes that the positive associations between each ecosystem dimension and venture density will be stronger in regions that have received the RIV designation, as the policy intervention would improve the efficiency with which these resources are leveraged. These moderation hypotheses are formally stated as:

H_4: RIV designation positively moderates the association between the Human & Knowledge Capability Dimension and deep tech venture density.

H_5: RIV designation positively moderates the association between the Financial & Infrastructure Capability Dimension and deep tech venture density.

H_6: RIV designation positively moderates the association between the Net-

work & Collaboration Capability Dimension and deep tech venture density.

Chapter 3

Methodology

3.1 Research Design

This study employs a quantitative cross-sectional research design at a harmonized regional level (combining NUTS 1 and NUTS 2 units) across the European Union. This methodological approach makes it possible to study how fixed, place-based ecosystem capabilities relate to differences in entrepreneurial outcomes across regions. The main outcome variable is Deep Tech Venture Density, measured at one point in time. Multiple Linear Regression (MLR) is used to test the main hypotheses (H1–H3) with statistical evidence. Interaction terms are added to the analysis to look at whether the RIV designation changes the strength of these relationships (H4–H6).

3.2 Data Sources and Operationalisation

This study uses two main datasets, which are combined using the harmonized regional NUTS code as a unique identifier. The regional level is chosen for the analysis because it captures local innovation patterns while still allowing for policy comparisons across the European Union.

Deep Tech Venture Density is the dependent variable in the study. It is measured as the number of deep tech startups per million people in each region. Using this measure helps to account for differences in population size and focuses on how efficiently ventures are clustered, rather than just counting the total number of companies.

Data for this variable comes from the European Patent Office (EPO) Deep Tech Finder platform, which provides figures up to 2025 (European Patent Office, 2023). This source is used because it offers a thorough and reliable listing of patent-backed ventures, along with detailed location data. The approach matches the patent-based measures used for the independent variables. The Deep Tech Finder combines information by linking European startups from Dealroom databases to the EPO's patent applicant records. This study also follows the EPO's method for defining Deep Tech Ventures, as described on their platform (European Patent Office, 2023).

Ventures are classified as Deep Tech if they have filed at least one European patent application and their inventions fall within one of the 30 technical domains delineated by EPO examiners. These domains address key European challenges, including quantum technology, core artificial intelligence, green steel, and gene therapy. The complete list of technical domains is presented in Appendix B. However, it must be acknowledged that, because of its patent-based nature, this definition excludes deep tech ventures that rely on trade secrets rather than patents (e.g. some pure AI/ML companies), potentially undercounting software-based deep tech. The findings of this study, therefore, are most applicable to 'hard' deep tech sectors (biotech, energy, quantum) that require formal IP protection.

To focus on new entrepreneurial activity, the sample prioritizes ventures in the Founding or Early Growth stages. However, to capture the extended commercialisation lifecycles characteristic of deep tech, the sample includes active deep tech SMEs that currently hold valid European patents and maintain SME status. This selection criterion prioritizes active commercial viability and patent maintenance over founding date, capturing the extended lifecycle inherent to deep tech commercialization, while large incumbents ($> 1,000$ employees) are explicitly omitted. Both university spin-offs and independent startups are included provided they satisfy the patent-based criteria. This selection process results in a sample of 6,955 deep-tech ventures. For each region, the count is normalised by the regional population in millions, using data from Eurostat.

The analysis in this study is based on the conceptual model from Chapter 2. Regional ecosystem strength is measured with three main dimensions thought to affect Deep Tech Venture Density: Human and Knowledge Capability, Financial and Infrastructure Capability, and Network and Commercialisation Capability, H, F, and N respectively. Each dimension is built using specific indicators from the European Commission's Regional Innovation Scoreboard and the Regional Innovation Index (RII), which offer highly standardised data for making solid comparisons between regions.

For every region, the raw values for these indicators are collected (see Table A.1 for indicator mapping). To make sure that scores are comparable and each indicator counts equally, the data is normalized using Min-Max scaling (from 0 to 1) across all regions. The final score for each dimension (H, F, and N) is then calculated as the simple average of its indicators.

This more detailed approach goes further than just using the overall RII, as it allows the analysis to identify which specific capability groups matter most for the presence of deep tech ventures. Importantly, the Financial Dimension is measured also using 'R&D expenditure in the business sector' as an indicator of how financially deep a region is (see Table A.1, Appendix A).While this metric primarily captures corporate balance sheet liquidity rather than Venture Capital availability, this choice is theoretically grounded in the 'Entrepreneurial Spawning' literature (Gompers et al., 2005). According to the Knowledge Spillover Theory of Entrepreneurship (KSTE), high levels of incumbent R&D generate a surplus of knowledge that established firms often fail to commercialize (Acs et al., 2009). This 'knowledge filter' creates an opportunity for employees to exit and establish new ventures (Klepper, 2001). Therefore, assuming efficient regional spillovers, aggregate corporate R&D stocks should theoretically serve as a leading indicator for the generation, and therefore presence, of investable deep tech opportunities.

The RIV designation is operationalized as a binary variable: regions officially participating in an RIV partnership are coded as 1, while all others are coded as 0. The RIV programme commenced in 2023, and although initial outcomes are expected to have come into effect already by 2025, its immediate effect on venture density may not yet be observable in the most recent data ((European Union, 2025)). The RIV variable serves as a proxy for EU-selected strategic priorities and shared policy frameworks, rather than a direct measure of policy outcomes. A significant moderating effect would indicate that regions prioritised by the EU exhibit distinct relationships between ecosystem resources and entrepreneurial outcomes.

Control variables are included to mitigate the risk of omitted variable bias, accounting for regional characteristics that influence entrepreneurship but are not captured by the primary innovation measures. Three principal factors, obtained from Eurostat at the NUTS level, are incorporated.

Regional GDP per capita, measured in purchasing power standards (PPS), is used to show the basic economic strength and market size of a region. Richer regions usually have more resources and advantages. Including this variable helps separate the general effects of wealth from the more specific effects of ecosystem capabilities, reducing the risk of missing important factors in the analysis.

Population density, measured as people per square kilometre, is used to capture the benefits of having multiple people and companies close together. Being close helps ideas spread more easily (Jaffe et al., 1993), which matches the knowledge spillover theory of entrepreneurship (KSTE) (Acs et al., 2009). By controlling for this, the analysis makes sure that the effect of Network and Commercialisation Capability (N) is about the quality of networks and policies, not just how close things are geographically.

A binary variable called γ_3NUTS1_Dummy is also included to control for differences in regional scale. This helps account for the size and policy differences between the larger NUTS 1 regions (coded as 1) and the smaller NUTS 2 regions (coded as 0).

3.3 Data Harmonization and NUTS Classification

Because the Regional Innovation Scoreboard (RIS) indicators are so important, and since data availability can vary, a careful data harmonization process was needed before bringing the datasets together. This step solved two main issues: the RIS uses several levels of regional classification, and it was important to ensure the Deep Tech Venture Density variable matched correctly with the harmonized regional units.

The RIS 2025 methodology uses a hybrid classification system. For some Member States, it relies on NUTS 1 regions because data at the NUTS 2 level, especially for survey-based indicators like the Community Innovation Survey, is not reliable enough (European Commission et al., 2025). To make results comparable and avoid the "Modifiable Areal Unit Problem" (MAUP), where results can change depending on the size and shape of regions (Openshaw, 1984), this study uses the exact RIS reporting units in their hybrid NUTS 1 and 2 forms as the unit of observation. This approach requires two different aggregation steps: In cases where the RIS applies NUTS 1 as the regional unit, such as in all regions of Belgium, Austria, France, and certain federal states in Germany, the Deep Tech Venture Count and the corresponding population figures from the underlying NUTS 2 regions were aggregated arithmetically. This approach was taken to construct a single, harmonized NUTS 1 unit for each relevant country. To make sure the new density measure takes population size into account, the final Deep Tech Venture Density for these harmonized regions was calculated by dividing the total venture count by the total population. This helps maintain the accuracy and fairness of the ratio. However, using combined NUTS 1/2 regions can create aggregation bias. For example, in large NUTS 1 areas, local hotspots of activity like university towns are averaged out across a bigger region. This can make the links between Human and Network capabilities and venture density look weaker than they really are, which is why the dummy variable γ_3NUTS1_Dummy was introduced.

Assignment to NUTS 1 or NUTS 2 status was based on an explicit look-up table derived from the official RIS regional list, rather than relying only on the length of the code string.This aims at preventing misclassification of single-region countries (e.g., CY0, LV0, LU0, MT0, EE0), which are technically NUTS 2 regions despite having a length of 3. The inclusion of γ_3NUTS1_Dummy in the regression models allows for the isolation of the specific ecosystem effects (H, F, N) from the inherent scale, administrative, and policy effects associated with analyzing larger regional units.

3.4 Empirical Model

Multiple Linear Regression (MLR) analysis is conducted utilizing R to assess the hypothesized relationships. The baseline model for hypotheses H1–H3 is specified as follows.

$$\text{Venture Density}_i = \beta_0 + \beta_1 H_i + \beta_2 F_i + \beta_3 N_i + \gamma_1 \text{GDP per capita}_i + \gamma_2 \text{Population Density}_i + \gamma_3 \text{NUTS1\_Dummy}_i + \epsilon_i \tag{1.1}$$

Here, H_i, F_i, and N_i represent the composite scores for the three ecosystem capability dimensions. γ_1 and γ_2 represent the coefficients for the two economic/locational control variables, and γ_3 represents the coefficient for the NUTS Level Status control variable. Unstandardized regression coefficients are reported to allow for tangible interpretation of the unit changes. For hypotheses H4–H6, interaction terms between the RIV dummy and each capability are introduced sequentially into the models.

$$\text{Venture Density}_i = [\text{baseline covariates}] + \beta_k \text{Capability}_i + \beta_{RIV} \text{RIV}_i + \beta_{Int}(\text{Capability}_i \times \text{RIV}_i) + \epsilon_i \tag{1.2}$$

While a standard Multiple Linear Regression (MLR) serves as the baseline specification, it is recognized that deep tech venture activity exhibits a highly skewed distribution (Figure D.1, Appendix D). As seen in Figure 4.2 a small number of 'Super-Hubs' create extreme variance that may induce heteroskedasticity and obscure relationships that exist for the majority of regions.

Consequently, this study employs a dual-specification approach. The Linear Model tests absolute effects, potentially heavily weighted by the largest regions. Complementing this, a Log-Transformed Model ($\ln(Y + 1)$) is utilized as a primary alternative specification. This transformation compresses the outliers as visualized in Figure 4.1b, allowing for the assessment of ecosystem elasticity across the average European region. When results are different, the Log-Transformed model is seen as showing how the ecosystem usually works for most of the data, without being affected by extreme outliers.

3.5 Analytical Procedure

Before building the model, the two main datasets (Deep Tech Venture Density and RIS indicators) are combined using matching regional NUTS codes. Data from the United Kingdom and Switzerland are deliberatly excluded. This is done to keep the data consistent and to make sure the analysis stays focused on the EU, which is the main goal of this study.

To create the three maindependent variables (H, F, and N), the original indicator values are first transformed. Each of the fifteen indicators is adjusted to a scale from 0 to 1 across the sample, so they can be compared easily. The overall scores for Human, Financial, and Network capabilities are then found by taking the simple average of their related indicators, following the groupings described in Chapter 2. While new scales are often checked for reliability using measures like Cronbach's alpha, this study uses indicators directly from the Regional Innovation Scoreboard (RIS) 2024/2025 framework. These indicators have already been checked and approved by the European Commission's Joint Research Centre (JRC) for both conceptual coherence and statistical reliability within the main innovation areas (European Commission, 2025). Consequently, the groupings are backed by both established EU policy methodology and the theoretical ecosystem dimensions.

The analysis begins with basic diagnostic procedures. Descriptive statistics such as means, standard deviations, minimum and maximum values, are calculated for all variables to give an overview of the dataset. Correlation matrices are used to look at the relationships between each predictor and the outcome variable. To check for multicollinearity, Variance Inflation Factors (VIFs) are calculated for H, F, N, and the two control variables, with a threshold of less than 5 to make sure multicollinearity is not a problem in the analysis.

Multiple Linear Regression models are run using R, and model fit is checked with the F-statistic. For hypotheses H1–H3, the main focus is on the t-statistics and p-values of the regression coefficients. For the moderation hypotheses (H4–H6), the key point is whether the interaction terms between the RIV dummy variable and each capability score are significant.

To ensure the statistical results are valid, the main assumptions of the Multiple Linear Regression model are checked. One key assumption is homoskedasticity, which means that the variance of the error terms (ϵ_i) should stay constant across all values of the independent variables. Because the regional data used here includes areas of different sizes and economic scales, it is expected that the data might show heteroskedasticity, or non-constant variance. If this is not addressed, it can lead to unreliable estimates and biased standard errors, making the hypothesis tests less trustworthy. The Breusch-Pagan test is used to formally check for homoskedasticity. To ensure the results are accurate no matter what this test shows, robust standard errors (White-Huber estimators) are used in all model versions. This way, the estimates of coefficients (βs) and their p-values stay reliable even if the assumption of homoskedasticity is not met.

3.6 Robustness Check

In addition to the standard diagnostic checks, a specific robustness test was carried out to address possible endogeneity in the Network dimension.

To check that the results were not caused by reverse causality, where innovation outputs might lead to venture creation instead of the other way around, a new measure of Network Connectivity Capital (N_Connect) was used. This version leaves out direct output indicators, such as PCT patent applications and design applications listed in

Table A.1 (Appendix A), and focuses only on collaboration structures. The baseline linear model was run again with this new measure. If the direction and significance of the coefficients are similar for both the original N and the new N_Connect variables, it shows that the main findings come from the ecosystem structure itself, not just from including patent data.

Chapter 4

Results

4.1 Descriptive Statistics and Correlations

Table 4.1: Descriptive Statistics ($N = 217$)

Variable	N	Mean	SD	Min	Max
Deep Tech Venture Density	217	8.94	12.67	0.00	77.86
Human Capability (H)	217	0.44	0.19	0.08	0.96
Financial Capability (F)	217	0.47	0.15	0.02	0.84
Network Capability (N)	217	0.52	0.16	0.16	0.86
RIV Designation (Dummy)	217	0.58	0.49	0.00	1.00
GDP per capita (10k PPS)	217	7.92	9.45	0.17	86.01
Pop. Density	217	352	861	3.5	7770

Table 4.2: Pearson Correlations

Variable	1	2	3	4
1. Deep Tech Density	1.00			
2. Human Cap.	0.67	1.00		
3. Financial Cap.	0.62	0.64	1.00	
4. Network Cap.	0.64	0.72	0.84	1.00

Table 4.1 presents the descriptive statistics for all variables. The dependent variable, Deep Tech Venture Density, shows extreme variance ($\mu = 8.94$, SD=12.67, range 0-77.86), confirming that deep tech activity is concentrated in pockets of high intensity rather than uniformly distributed. Among the ecosystem dimensions (scaled 0-1), Network Capability is the most prevalent asset ($\mu = 0.52$), followed by Financial ($\mu = 0.47$) and Human ($\mu = 0.44$) capabilities. The sample is structurally diverse. 58% of regions hold the RIV designation, and control variables span the full spectrum from rural peripheries (Pop Density: 3.5) to major metropolitan hubs (Pop Density: 7,770).

To contextualize this heterogeneity, two supplementary visualizations are provided. Appendix D (Figure D.1) ranks the top 100 regions and reveals a distinct ”long tail” distribution, where a small minority of elite regions drive the aggregate density. The spatial analysis in Appendix E (Figure E.1) visually confirms the existence of ”Super-Hubs” such as Stockholm and Helsinki, which stand as islands of high activity amid broader areas of lower density.

Table 4.2 displays the Pearson correlations. As anticipated, Deep Tech Density correlates positively with all three dimensions: Human ($r = 0.67$), Network ($r = 0.64$), and Financial ($r = 0.62$). While the inter-correlation between Financial and Network Capability is high ($r = 0.84$), the Variance Inflation Factors reported in Appendix C (Table C.2) confirm that this does not exceed the threshold for severe multicollinearity, ensuring regression stability.

4.2 Regression Analysis

Table 4.3: Regression Analysis of Deep Tech Venture Density (HC3 Robust Errors)

	DV: Deep Tech Venture Density				ln(**DTVD** + 1)
Predictors	**Model 1** (Baseline)	**Model 2** (Mod. H4)	**Model 3** (Mod. H5)	**Model 4** (Mod. H6)	**Model 5** (Log-Linear)
Constant	−17.832*** (2.994)	−15.848*** (3.785)	−12.389*** (3.563)	−12.045*** (3.483)	−1.354*** (0.145)
H Capability (H_1)	31.157*** (6.758)	25.052** (11.254)	30.557*** (7.093)	30.552*** (7.052)	2.299*** (0.324)
F Capability (H_2)	15.382* (8.135)	14.975* (8.094)	2.545 (9.234)	15.063* (7.905)	0.464 (0.619)
N Capability (H_3)	10.186 (7.275)	10.053 (7.678)	10.209 (7.706)	−1.897 (9.242)	3.142*** (0.558)
Moderators & Controls					
RIV Designation (Dummy)		−3.271 (4.668)	−8.902 (5.415)	−9.320* (4.807)	
H Cap × RIV (**H_4**)		10.332 (12.990)			
F Cap × RIV (**H_5**)			21.322 (12.936)		
N Cap × RIV (**H_6**)				20.321* (10.620)	
GDP per capita (10k PPS)	0.075 (0.081)	0.074 (0.095)	0.077 (0.093)	0.079 (0.096)	0.012* (0.006)
Pop Density	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.000*** (0.000)
NUTS1 Dummy	2.891** (1.439)	3.032** (1.472)	3.029** (1.388)	3.095** (1.405)	0.553*** (0.162)
Model Fit					
Observations	217	217	217	217	217
R^2	0.533	0.540	0.549	0.550	0.711
Adjusted R^2	0.519	0.522	0.532	0.532	0.702

Robust Standard Errors (HC3) in parentheses. Negative constants reflect intercept positioning outside observable data range. Significance: *p<0.1; **p<0.05; ***p<0.01. Model 5 uses log-transformed dependent variable.

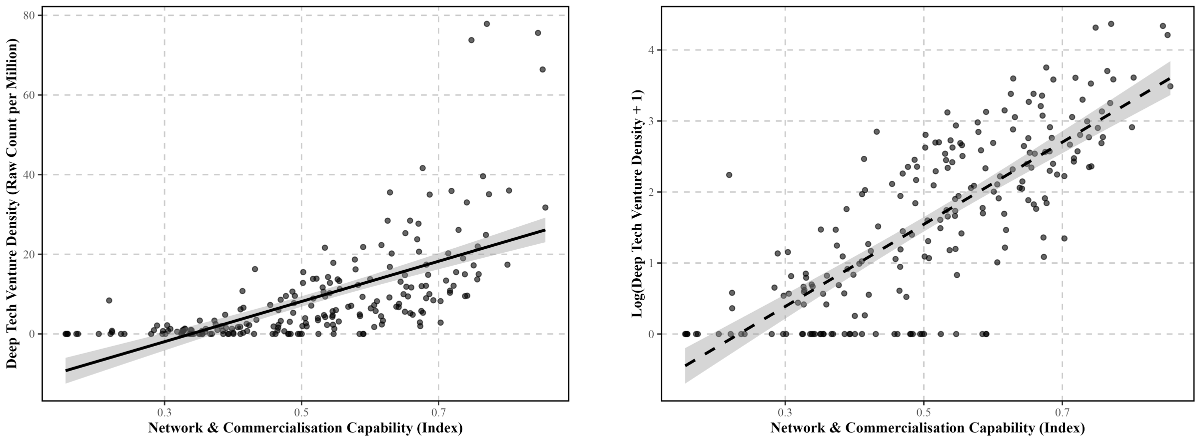
4.2.1 Baseline Model Results (Hypotheses H1–H3)

The baseline model (Model 1) tests the direct relationship between the three ecosystem capability dimensions and Deep Tech Venture Density. To distinguish between additive effects (absolute venture yield) and multiplicative effects (proportional growth), the analysis reports coefficients from both the baseline Linear Model (Model 1) and the Log-Transformed Model (Model 5).

Hypothesis 1 (Human & Knowledge Capability): The analysis reveals a positive and highly significant relationship between Human Capability and venture density across all specifications. In the linear model, the coefficient is large and significant ($\beta = 31.157, p < 0.01$), and this significance is maintained in the log-transformed specification ($\beta = 2.299, p < 0.001$). This stability shows that the link between talent stocks and venture density remains strong across different models. Human Capability stands out because it not only adds to the total number of ventures but also keeps a steady elastic effect, meaning that percentage increases in talent lead to similar percentage increases in density. This makes human capital a key factor in ecosystem performance, regardless of region size or how talent is distributed. Therefore, H1 is strongly supported.

Hypothesis 2 (Financial & Infrastructure Capability): The results for Financial Capability exhibit sensitivity to model specification. In the linear model, the relationship is positive and marginally significant ($\beta = 15.382, p < 0.1$). However, in the log-transformed model, the effect is not significant ($\beta = 0.464, p = 0.440$). This means Financial Capability has a weak additive effect and is inelastic. Regional investment, measured by Corporate R&D, may help increase the number of ventures in large hubs, but it does not act as a scalable factor for the whole sample. The lack of significance in the log model shows that more investment does not lead to proportional increases in venture density. This suggests that corporate financial inputs are more like fixed resources than factors that multiply over time. Unlike venture capital, internal corporate R&D seems to have diminishing returns for ecosystem density, showing blocked spillovers where corporate wealth does not efficiently grow the number of independent ventures. Therefore, H2 is only weakly supported and depends on the model used.

Hypothesis 3 (Network & Collaboration Capability): The analysis shows a difference in how Network Capability functions. In the linear baseline, the coefficient is positive but not statistically significant ($\beta = 10.186, p > 0.1$). This means networks do not provide a consistent added benefit across the sample's varied distribution. However, in the log-transformed model, Network Capability becomes a highly significant predictor ($\beta = 3.142, p < 0.001$). This discrepancy confirms evidence of non-linear elasticity. The significance of the log-linear coefficient implies constant semi-elasticity: a unit improvement in network connectivity results in a consistent relative (percentage) increase in venture density, regardless of the region's initial size. Consequently, the lack of significance in the linear model is attributed to heteroscedasticity, visualized in Figure 4.1 and in Appendix D (Figure D.1)), where the absolute impact of networks in smaller regions is statistically obscured by the magnitude of effects in larger hubs. Thus, H3 is supported, confirming networks as a multiplicative driver of density.



(a) Raw Scale (Baseline Model)

(b) Log-Transformed Scale

Figure 4.1: **The Unmasking of Network Capability.** (a) In the raw scale, the linear relationship is obscured by extreme outliers ("Super-Hubs") and high variance (heteroskedasticity), resulting in statistical insignificance. (b) Transforming the dependent variable reveals a robust, linear relationship ($p < 0.001$) across the entire distribution. This visually confirms that Network Capability is a significant driver for the majority of European regions, not just the elite hubs.

Among the control variables, in the linear model the *NUTS1 Dummy* is positive and significant ($\beta \approx 2.89, p < 0.05$). Crucially, in the log-transformed specification, it becomes highly significant (p¡0.001). This confirms that administrative scale systematically affects density measures, with larger NUTS 1 regions reporting artificially higher aggregate figures. The significance of this control validates the decision to include it, ensuring that the reported effects of ecosystem capabilities are net of these administrative scale distortions. The role of regional wealth (*GDP per capita*) exhibits a functional divergence similar to Network Capability. In the linear baseline, GDP per capita is statistically insignificant (p¿0.1), suggesting that pure economic wealth does not linearly drive the absolute clustering of deep tech ventures. However, in the log-transformed model, GDP becomes a significant predictor (p=0.028). This indicates that while wealth alone cannot generate "Super-Hub" levels of density (additive effect), it is a significant factor in enabling proportional ecosystem growth (elasticity) for the average region. Finally, *Population Density* exhibits a negative coefficient, significant only in the log-specification, suggesting that deep tech density per million inhabitants does not scale linearly with simple urban agglomeration.

4.2.2 Moderation Analysis (Hypotheses H4–H6)

Models 2, 3, and 4 introduce the interaction terms to test whether the RIV designation moderates the relationship between ecosystem capabilities and venture density. The inclusion of interaction terms improved the explanatory power of the model, raising the Adjusted R^2 from 0.519 (Baseline) to 0.532 (Model 4).

Hypothesis 4 (Moderation of Human Capability): In Model 2, the interaction term between Human Capability and RIV designation is positive but not statistically significant ($\beta = 10.332, p > 0.1$). This implies that the effect of human capital on venture density does not significantly differ between RIV-designated and non-designated regions. This null result reinforces the finding from H1 that Human Capital is a structural driver with a stable slope, resistant to short-term policy modulation. Thus, H4 is not supported.

Hypothesis 5 (Moderation of Financial Capability): In Model 3, the interaction term for Financial Capability is positive ($\beta = 21.322$) but marginally fails to reach statistical significance (p=0.101). Despite the magnitude of the coefficient, the large standard errors indicate high variability in how RIV regions leverage financial assets. This suggests that the RIV designation alone is insufficient to systematically unlock the efficiency of financial inputs across the group; rather, financial performance appears idiosyncratic to specific hubs rather than a generalized feature of the designation. Consequently, there is no statistical evidence of a moderation effect. Thus, H5 is not supported.

Hypothesis 6 (Moderation of Network Capability): In Model 4, the interaction term between Network Capability and RIV designation is positive and marginally significant ($\beta = 20.321, p < 0.1$). This indicates that the relationship between Network Capability and Deep Tech Density is significantly stronger in regions holding the RIV designation. When considered together with the log-model findings (H3), this interaction clarifies how the network capability operates in practice. Although networks tend to produce a proportional percentage increase across all regions, it is in the areas designated as RIV that this proportional growth leads to noticeable absolute gains. This suggests that the impact of network effects is not uniform but depends on other characteristics of the region. In non-RIV regions, which may have smaller base densities, the additive yield is statistically indistinguishable from zero ($\beta = -1.897, p > 0.1$) in a linear model, despite the underlying multiplicative mechanism being active. Thus, given the marginal significance level, H6 is partially supported.

To further illustrate this significant interaction, Figure 4.2 plots the predicted relationship between Network Capability and Deep Tech Venture Density. The slope for RIV-designated regions (solid line) is positive, confirming that within this subsample, higher network connectivity is associated with higher absolute venture counts

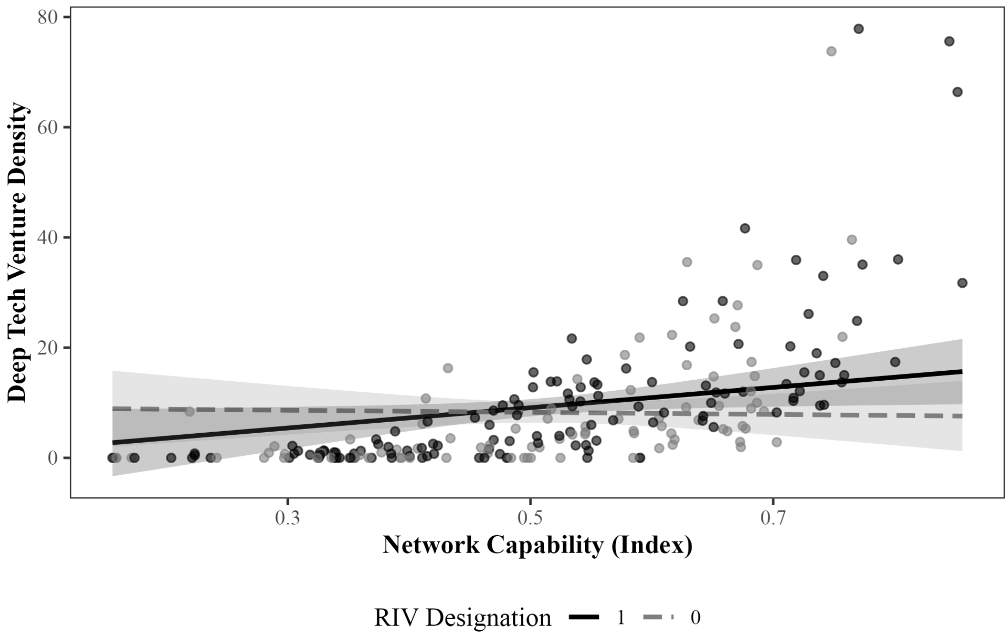


Figure 4.2: **Interaction Effect of RIV Designation and Network Capability.** The plot illustrates the predicted Deep Tech Venture Density across levels of Network Capability for RIV-designated regions (solid line) versus non-designated regions (dashed line).

4.3 Robustness Checks

4.3.1 Alternative Operationalization of Networks

To ensure the observed network effects were not confounded by intellectual property stocks, the Network Capability measure was substituted with an alternative indicator ($N\_Connect$) that excludes patent outputs. The results (provided in Appendix C, Table C.1) remained consistent with the baseline model: Human Capability remained highly significant, while the alternative network measure remained insignificant as a direct predictor in the linear specification. This confirms that the baseline findings are insensitive to minor variations in the operationalization of network quality.

4.3.2 Diagnostic Validation and Heteroskedasticity

To verify the statistical validity of the regression estimates, a series of post-estimation diagnostics were performed on the baseline models. First, the Variance Inflation Factor (VIF) test confirmed that multicollinearity is not a concern, with all variance inflation factors falling well below the critical threshold of 5 (Mean VIF = 2.408) (Appendix C, Table C.2).

Second, the Breusch-Pagan test (Appendix C, Table C.3) rejected the null hypothesis of homoskedasticity for both the linear ($BP = 36.79, p < 0.001$) and log-transformed ($BP = 20.56, p < 0.01$) specifications. This confirms the presence of non-constant variance driven by the "Super-Hub" outliers identified in Figure 4.2. To make sure results would be reliable, all models were re-estimated using Huber-White (HC3) Robust Standard Errors. The significance of the key predictors remained consistent after this adjustment. This finding further strengthens the support to the core hypotheses of the study and suggests that the results are not influenced by violations of standard error assumptions.

Chapter 5

Discussion and Conclusions

5.1 Introduction

This thesis set out to examine the factors that contribute to the presence and clustering of deep tech ventures, and to assess the effectiveness of strategic policy interventions in the European Union. The central research question guiding this investigation was:

> *How do regional innovation ecosystem capabilities explain the regional variation in the density of active deep tech ventures, and how does the Regional Innovation Valley designation moderate these relationships?*

The analysis of 217 European regions produced three main findings, as illustrated in figure 5.1. First, Human Capability appears to be an essential driver for the development of deep tech clusters, consistently acting as a limiting factor for ecosystem performance across all models. In contrast, the significance of Network Capability varies depending on the model specification, but Human Capability remains a stable and fundamental determinant. Second, Network Capability seems to function as a driver of efficiency for the average region. While its effect is less apparent in baseline models, likely due to the influence of elite hubs, it becomes more pronounced when policy coordination is present. Third, the RIV designation may serve as an efficiency signal and a mechanism for cohesion, particularly in regions with lower initial densities, where it appears to help unlock network potential.

This chapter examines these findings in the context of existing ecosystem theory, considers their potential implications for policy and practice, notes the methodological limitations of the analysis, and offers suggestions for future research.

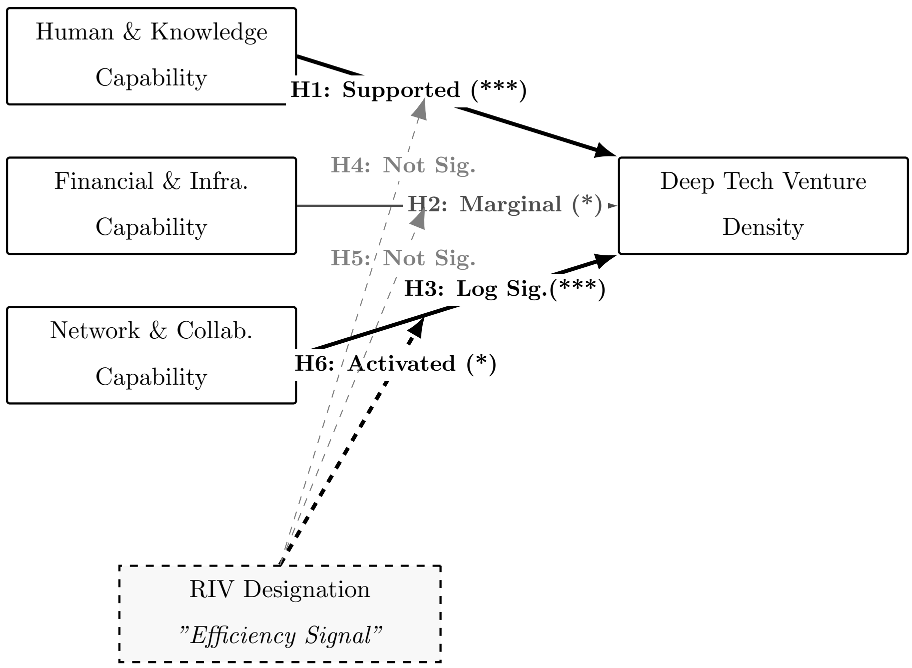


Figure 5.1: **Summary of Findings.** This diagram shows the ecosystem hierarchy. Bold solid lines show strong direct effects, while bold dashed lines show strong policy activation. Faded or thin dashed lines represent weak or insignificant relationships.

5.2 Discussion of Findings and Theoretical Implications

5.2.1 The Nature of Human Capital (H1 & H4)

The analysis suggests a clear hierarchy of the ecosystem capabilities, with Human and Knowledge Capability as a fundamental driver. The coefficient for this dimension is consistently positive and statistically significant ($p < 0.01$) across all model specifications. This finding provides some support for the Knowledge Spillover Theory of Entrepreneurship (KSTE), since it suggests that regional knowledge stock may be the main channel through which entrepreneurial opportunities are identified and exploited (Audretsch and Lehmann, 2005).

The stability of this effect both in linear and log models suggests that the relationship between specialized talent and deep tech density is both fundamental and responsive. Increases in the talent base of a region therefore appear to be associated with proportional increases in venture density.

On the other hand, the insignificance of the interaction between Human Capability and the RIV policy (H4) reveals a potential limitation of policy initiatives. While the literature suggests policy designations can signal and attract talent by reducing information asymmetries (Kelchtermans et al., 2025), this effect was not observed in this study. The null result implies that the RIV label's signal is insufficient to overcome the friction in mobilizing high-level human capital.

This contrast highlights that Human Capital functions as a persistent structural asset. In deep tech, a sufficient pool of specialized talent, such as PhDs and researchers, is required and cannot be quickly increased or shifted through short-term policy measures. Although the RIV designation was expected to improve visibility, it does not overcome the time and effort needed to develop or attract advanced human capital. As a result, Human Capability acts as a fixed constraint on ecosystem performance, unlike other dimensions that may be more easily influenced by policy.

5.2.2 Financial Inelasticity and Blocked Spillovers (H2 & H5)

Although the literature defines deep tech ventures by high capital intensity and long development cycles (Grande et al., 2025), our results offer only limited, conditional support for the impact of regional financial depth (H2). The loss of significance in the log-transformed model ($p > 0.1$) suggests that Financial Capability is inelastic. Unlike human capital, greater regional investment does not lead to proportional increases in venture density. This refines the "threshold condition" theory (Hall, 2010): while a basic level of economic infrastructure is likely required, treating aggregate financial depth as a linear driver of ecosystem performance is analytically unsound.

This finding provides an interesting insight into Entrepreneurial Spawning. According to the "Xerox View", high levels of corporate R&D spending could theoretically serve as a leading indicator for venture formation, as employees leave incumbent firms to commercialize unused knowledge spillovers (Klepper, 2001; Gompers et al., 2005). However, the null result here suggests that spillovers are blocked. It appears that, unlike in the US, European corporate R&D remains confined within incumbent firms. Although the region appears wealthy in aggregate data, that wealth does not seem to be accessible to entrepreneurial agents. This challenges the assumption that corporate R&D acts as a valid proxy for ecosystem vitality.

Furthermore, the insignificant interaction term for the moderation hypothesis (H5), indicates that the effect of the RIV designation on financial efficiency is inconsistent. This highlights a key limitation of place-based policy. While public actors can coordinate public aspects such as networks, they have limited influence over the allocation of private corporate capital. The RIV label alone does not appear sufficient to unlock internal corporate funds or change the investment approach of private market actors.

Ultimately, these findings reinforce the "financial paradox" in innovation geography (Hall and Lerner, 2010). Unlike Human Capability, which is "sticky" and tied to location, financial capital is mobile. High-potential deep tech ventures can attract investment from global hubs regardless of location, making local corporate stocks less predictive of venture presence than the availability of local talent.

5.2.3 Network Elasticity and the Multiplier Effect (H3 & H6)

The findings related to the Network & Collaboration Dimension provide an important clarification to ecosystem theory by addressing the issue of 'Super-Hub Bias' that is frequently observed in aggregate studies. Although previous research has described networks as the basic infrastructure of innovation (Audretsch et al., 2022), the present analysis indicates that their influence is not linear in nature.

Network Capability did not show statistical significance in the initial linear model, but became a highly significant predictor ($p < 0.001$) when the log-transformed model was used. This difference suggests that networks contribute to ecosystem outcomes in a multiplicative way, rather than simply adding to the total. In contrast to Human Capital (H1), which increases venture counts directly, Network Capability appears to improve the efficiency of the ecosystem by a constant percentage. The lack of significance in the linear model can be explained by heteroskedasticity, where the large absolute values in 'Super-Hubs' obscure the relative efficiency of smaller regions. Figure 4.1 illustrates this point: Panel (a) shows that outliers dominate the noise, while Panel (b) demonstrates a clearer linear and positive relationship after adjusting for scale.

The moderation analysis (H6) supports this interpretation. The positive interaction between Network Capability and RIV designation ($p < 0.1$) shows that the effect of network potential on venture density is stronger in regions with RIV status. This finding indicates that the RIV policy may enhance the effectiveness of network infrastructure. In non-RIV regions, the network infrastructure is present, but its impact is less visible due to statistical noise. The RIV designation, by promoting collaboration and providing a formal structure (Kelchtermans et al., 2025), appears to strengthen these connections and make the benefits of networks more apparent.

The negative main effect of the RIV dummy (β9.3) should not be interpreted as evidence that the policy is detrimental. Instead, this result likely reflects a selection mechanism. Regions that are already established 'Super-Hubs' with high density tend to rely on existing networks and may not see the need for the additional administrative requirements of RIV designation. In contrast, regions with lower initial density but greater ambition are more likely to pursue RIV status to access funding and formal structure. As a result, the RIV group aggregates regions with high potential but lower current density. The policy appears to be effective by increasing the rate of growth in these regions, rather than causing an immediate increase in their starting point.

5.2.4 Control Variables and Regional Heterogeneity

The analysis of control variables validates the methodological choice to account for regional scale and provides further nuance to the geography of deep tech.

The NUTS1 dummy variable is found to be positive and significant in all model specifications, with its significance increasing further in the log-transformed model (p¡0.001). This result shows that the size of administrative regions can create a systematic bias in density measures. Larger regions like NUTS 1 often report higher total values than smaller regions like NUTS 2. As a result, some of the differences seen in density may be due to the way administrative boundaries are drawn, not just real economic or structural differences. The fact that this control variable is significant supports the strength of the model. By adjusting for these administrative effects, the model makes sure that the impact of ecosystem capabilities (H1-H3) reflects actual structural strengths in the local economy, rather than just being shaped by map boundaries.

Regional wealth, measured by GDP, shows a similar trend to Network Capability, as there is a clear difference between the linear and log-transformed models. In the linear model, the lack of statistical significance ($p > 0.1$) indicates that higher economic output alone does not directly lead to the creation of "Super-Hubs." This means that simply having a wealthy economy does not guarantee the development of a concentrated cluster of deep tech companies. On the other hand, in the log-transformed model, regional wealth becomes statistically significant ($p = 0.028$), suggesting it may play a supportive role. While financial resources alone may not be enough to build a deep tech ecosystem, reaching a certain level of regional prosperity could help turn existing strengths into new ventures.

One interesting finding is that the negative and significant coefficient for Population Density in the log-specifications suggests that deep tech might not necessarily follow the typical urban agglomeration model. Unlike digital applications or SaaS ventures (e.g sharing platforms like Uber), which tend to concentrate in hyper-dense metropolises like Berlin or London to access large consumer markets (Florida, 2017), deep tech ventures exhibit a different location logic. In fact, these ventures appear to prioritize proximity to specific technical assets like university campuses and industrial research parks, over general urban density, a pattern consistent with the localization aspect of knowledge spillovers (Audretsch and Lehmann, 2005). Supporting research by Romme (2022) shows that high-tech clusters frequently emerge in smaller, specialized municipalities like Eindhoven rather than exclusively in capital cities. The observation of this control variable hints that, in the case of deep tech, the concentration of relevant expertise may be more critical than the overall size of the surrounding population.

5.3 Strategic Implications for Practice and Policy

The findings suggest a framework that may help in identifying which ecosystem capabilities could be influenced through policy intervention, as well as offering some guidance on how stakeholders might consider optimizing resource allocation or venture creation and localization.

5.3.1 For Entrepreneurs and Investors

Although the Regional Innovation Valley (RIV) designation is primarily a public policy tool, its link to network efficiency offers valuable insights for corporate strategy. For Multinational Enterprises (MNCs) and Corporate Venture Capital (CVC) units, RIV-designated regions offer higher network conversion rates and policy-backed collaboration. The positive interaction effect (H6) shows that these regions have strong knowledge transfer mechanisms in place, which makes them well-suited for open innovation strategies that depend on collaboration with local partners.

For stakeholders who value the importance of network and collaboration, higher marginal returns on investment could be found in these emerging ecosystems. Investors seeking deep tech assets should consider the RIV label a reliable indicator of lower collaboration costs. The designation helps identify undervalued regions with sufficient network density to support scaling, even if their total venture numbers are lower than major capitals. This presents a strategic opportunity to access strong innovation networks before markets become saturated.

5.3.2 Policy Levers and Structural Constraints

To influence Deep Tech Venture Density, practitioners should distinguish between policy-elastic variables and structural constraints. Results indicate that connectivity is a flexible asset that responds to intervention (H6). Regional Development Agencies can enhance connectivity by supporting collaboration initiatives and funding collaborative platforms. In contrast, regional talent stocks (Human Capital) are structurally inelastic (H4). These assets rely on long-term institutional attractiveness and education policy, making them resistant to short-term innovation designations and positioning them as long-term objectives. The Commission should therefore use the RIV label as a tool for regional cohesion. Regional policymakers should avoid resource misallocation. For instance, investing in network-building may yield limited returns in regions lacking sufficient Human Capital, as connectivity cannot compensate for a talent deficit. RIV status is most effective as an activation mechanism for regions with strong talent bases but limited startup activity.

5.4 Reflections on Validity and Reliability

The accuracy of these findings relies on properly accounting for differences across regions. In the linear model, Network Capability did not appear significant, but this was because the data included extreme outliers that skewed the results. Applying a log transformation helped ensure that the results better represent the wider range of European regions, without being overly influenced by major capitals.

Including specific control variables made the model stronger. For instance, Population Density helped separate the effects of city size, so the network results (H3) reflect actual connectivity, not just physical proximity. The NUTS Dummy showed that the model adjusted for differences in administrative size, helping to avoid the Modifiable Areal Unit Problem.

A strong link between Financial and Network capabilities ($r = 0.84$) could have threatened the validity of the model. However, Variance Inflation Factors (see Appendix C, Table C.2) showed the model was stable. In fact, the RIV interaction was significant for Network Capability (H6) but not for Financial Capability (H5), which supports the model's ability to tell these factors apart.

5.5 Limitations and Future Research

This study provides robust empirical evidence on the hierarchy of ecosystem assets; however, the findings must be interpreted within the context of specific methodological and conceptual limitations.

A primary limitation of this study is its cross-sectional design. While the RIV designation is associated with higher network efficiency, the temporal mismatch between the policy's recent commencement (2023) and the data collection period (up to 2025) complicates causal inference. Specifically, because the dependent variable measures venture presence (active firms) rather than solely venture emergence (new firms), the observed density may reflect a combination of indigenous venture creation, the attraction of migratory firms, and the retention of existing scale-ups. Therefore, the significant coefficients for RIV should not be interpreted as the policy 'creating' ventures, but rather as the policy successfully identifying and clustering regions with high pre-existing structural potential. The RIV designation serves as a valid proxy for 'high-potential ecosystems' rather than a treatment effect.

Deep Tech Venture Density is measured using EPO patent data. This choice makes it possible to reliably identify ventures that are focused on scientific and technical breakthroughs, but it also limits the range of technologies covered. The method mainly captures "Hard Deep Tech" sectors, such as biotechnology, quantum computing, and energy, where patenting is the norm. As a result, it likely underrepresents "Soft Deep Tech" ventures, like generative AI and advanced SaaS, which often depend more on trade secrets or quick execution than on patents.

Because the sample is focused on capital-intensive sectors, the lack of a significant result for Financial Capability (H2) is particularly noteworthy. If regional financial depth were an important factor, it would likely have shown up in this hardware-focused group. The fact that it did not supports the idea of blocked spillovers, suggesting that total corporate R&D is not a good stand-in for the specific, accessible risk capital that deep tech firms actually need.

One important limitation is how Financial Capability is measured, as it relies on RIS indicators like R&D spending in the business sector. This metric primarily captures corporate balance sheet liquidity and internal investment by established firms. While this choice was theoretically grounded in the "Entrepreneurial Spawning" literature (Gompers et al., 2005; Klepper, 2001), which suggests that corporate R&D stocks should act as a reservoir for future spin-offs, the null result indicates that this mechanism is largely inoperative in the sample. Consequently, the lack of statistical significance reflects a phenomenon of blocked spillovers: the model captures the region's aggregate wealth, but this corporate capital appears structurally disconnected from the specific, external risk capital required to fuel independent deep tech formation.

The use of harmonized NUTS 1 and NUTS 2 regions introduces the Modifiable Areal Unit Problem (MAUP). For the NUTS 1 units in the sample (e.g., broad German federal states), the averaging of Human and Network capabilities across large geographic areas may dilute the signal of localized innovation clusters (e.g., a specific university town). This "smoothing effect" suggests that the reported coefficients for Human Capability are likely conservative estimates, as the true impact of talent density is often more concentrated than the regional average suggests. The inclusion of the *NUTS1 Dummy* control mitigates, but does not fully eliminate, this aggregation bias.

While this study controlled for spatial heterogeneity via NUTS dummies and population density, the regression analysis treats regions as independent units. However, the spatial clustering observed in the visual analysis suggests the presence of spatial spillovers, where smaller regions may benefit from the ecosystem assets of neighboring hubs ("borrowed size"). Future research should explicitly model these dependencies using Spatial Autoregressive (SAR) or Spatial Error Models (SEM). This approach would measure how much a region's deep tech activity is affected by what nearby regions can do. It would help show the 'Network Multiplier' effect that goes beyond official borders.

There are two more measurement limitations to consider. First, the "Headquarters Effect" can create spatial bias. Many companies register their headquarters in capital cities for administrative reasons, but do most of their R&D in university towns elsewhere. This can make administrative centers seem more active than they really are, while the regions where innovation actually happens may be overlooked.

Second, the study aggregates all "Deep Tech" fields, despite the existence of more than 30 distinct technical areas. Consequently, the model is limited to identifying only the average drivers of the ecosystem, thereby obscuring the specific requirements and challenges unique to each field. For instance, semiconductor manufacturing is characterized by a high demand for financial investment, whereas the development of AI software is more dependent on access to specialized human capital. The current model, however, does not differentiate between these varying needs and instead treats all fields as if they are subject to the same conditions.

In order to more accurately determine causality, future research should consider employing a Difference-in-Differences (DiD) approach once a sufficient period has elapsed following the implementation of the policy, which is likely to be feasible by 2027 or 2028. This methodology would facilitate the isolation of the specific effects attributable to the RIV policy from broader regional trends.Additionally, future studies should integrate private equity databases (e.g., Dealroom, Crunchbase) to distinguish between static corporate R&D and fluid Venture Capital deployment. This would allow for testing if the 'Hierarchy of Assets' remains stable across different funding lifecycles or if specific drivers (e.g., Finance) become significant for capital-intensive verticals.

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Chapter A

Appendix A: Variable Definitions

This appendix details the construction of the composite ecosystem dimensions used in the analysis. Table A.1 lists the individual indicators selected from the Regional Innovation Scoreboard (RIS 2024), their mapping to the three capability dimensions, and the theoretical rationale for their inclusion.

Table A.1: Construction of Regional Ecosystem Dimensions from RIS Indicators

Construct	Code	Indicator Description	Rationale
Human & Knowledge (H)	1.1.2	Population with tertiary education	Measures the supply of advanced skills in the 25-34 age group. Operationalized as a proxy for the pool of talent available to understand and create new technologies.
	1.1.3	Lifelong learning participation	Captures the share of adults (25-64) updating their skills. Serves as an indicator of workforce adaptability and how well the region keeps up with changing requirements.
	1.2.1	International scientific co-publications	Measures research involving foreign partners. Selected to proxy the quality and status of local researchers.
	1.2.2	Scientific publications (top 10% cited)	Measures the volume of highly cited research. Operationalized as the stock of high-quality science that serves as the raw material for deep tech ventures.
	2.1.1	R&D expenditure in public sector	Measures government and university investment. Categorized here to separate the source of scientific knowledge (public) from commercial application (private).
	2.3.2	Employed ICT specialists	Measures employment in the IT sector. Serves as a specific proxy for the technical digital talent needed to build complex software and systems.
Financial & Infra. (F)	2.2.1	R&D expenditure in business sector	Measures corporate investment in R&D. Placed here to explicitly test the role of private sector knowledge creation as a distinct input from public research.
	2.2.2	Non-R&D innovation expenditures	Captures SME spending on machinery and equipment. Used to proxy the financial resources spent on applying technology rather than just inventing it.

Construct	Code	Indicator Description	Rationale
	2.2.3	Innovation expenditures per employee	Measures monetary input for innovation in SMEs. Serves as a proxy for the financial strength and investment capacity of local firms.
	2.3.1	Cloud computing in enterprises	Measures the use of cloud services. Proxies access to modern, scalable digital infrastructure.
Network & Collab. (N)	1.3.1	Broadband penetration	Measures household internet access. Proxies the physical infrastructure needed to share information quickly.
	3.1.1	SMEs introducing innovations	Measures SMEs launching new products. Operationalized to reflect an active market where ideas are frequently tested and shared.
	3.2.1	Innovative SMEs collaborating	Measures formal agreements between firms. Serves as a direct indicator of how much companies are willing to share knowledge with partners.
	3.2.2	Public-private co-publications	Measures joint research between companies and universities. Included to capture the bridge between academia and industry.
	3.3.1	PCT patent applications	Measures international patent filings. Categorized here as a tradable asset that facilitates licensing and technology transfer between actors.
	3.3.3	Design applications	Measures design protections. Proxies commercial activity, showing that technical knowledge is being packaged for sale in the market.

Chapter B

Appendix B: EPO Deep Tech Technical Fields

The following list details the specific technical domains used to classify deep tech ventures in this study, as defined by the European Patent Office (EPO) Deep Tech Finder platform.

- **Clean Energy - End Use**
  - Carbon capture & storage
  - Green cement
  - Green steel
- **Clean Energy - Grid**
  - Physical Grid
  - Smart EV
  - Smart Grid
- **Clean Energy - Production**
  - Electrolysis
  - Offshore wind energy
  - Solar - Applications
  - Solar - Devices
  - Solar - Management
  - Solar - Materials
- **Clean Energy - Storage**
  - Battery recycling
  - Lithium and lithium-ion
  - Mechanical
  - Other chemistries
  - Redox flow
  - Sodium-ion
  - Solid state
  - Supercapacitors
- **Digital Agriculture**
  - Animal husbandry
  - Plant agriculture
- **Oncology - ICT**
  - Bioinformatics
  - Healthcare informatics
- **Oncology - Cancer Models**
  - Cancer models
- **Oncology - Diagnostics**
  - Biopsies
  - Imaging
  - Personalised medicine

- **Oncology - Treatment**
  - Alternative treatments
  - Classical chemotherapy
  - Gene therapy
  - Hormonal therapy
  - Immunotherapy
  - Mitigating side-effects
  - Non-coding nucleic acids
  - Other physical treatments
  - Radiotherapy
  - Surgery
  - Targeted chemotherapy
- **Plastics**
  - Alternative Plastics
  - Recovery
  - Recycling
- **Quantum**
  - Quantum
- **Smart Industry - Applications**
  - Business services
  - Consumer goods
  - Healthcare
  - Home
  - Industrial applications
  - Infrastructure
  - Vehicles
- **Smart Industry - Core**
  - Connectivity
  - IT Software
  - IT hardware
- **Smart Industry - Enabling**
  - 3D support systems
  - Core AI
  - Data management
  - Data security
  - Geo-positioning
  - Power supply
  - Safety
  - User interface
- **Space Technologies**
  - Propulsion
- **Water Tech**
  - Efficient water use
  - Potable water harvesting
  - Protection against water
  - Water treatment

Chapter C

Appendix C: Robustness Checks

This appendix provides supplementary analyses to verify the stability and validity of the main regression results reported in Chapter 4. Section C.1 presents the results using an alternative network measure, while Section C.2 details the post-estimation diagnostics for multicollinearity and heteroskedasticity.

C.1 Alternative Network Measure

To ensure the observed network effects were not confounded by intellectual property stocks, the Network Capability measure was substituted with an alternative indicator (*N_Connect*) that excludes patent outputs. Table C.1 presents the results of this alternative specification.

Table C.1: Robustness Check: Alternative Network Measure (N_Connect)

	Dependent Variable: Deep Tech Venture Density				
	Estimate	**Std. Error**	**t value**	**Pr(> $\|t\|$)**	**Signif.**
Intercept	−16.749***	(2.822)	−5.936	< 0.001	***
H_Capability	34.223***	(6.824)	5.015	< 0.001	***
F_Capability	23.731**	(8.153)	2.911	0.004	**
N_Connect	**−2.277**	**(7.006)**	**−0.325**	**0.746**	
GDP_PPS_2023	0.000	(0.000)	1.540	0.125	
Pop_Density	−0.001*	(0.001)	−1.731	0.085	*
Nuts_Dummy	2.515*	(1.358)	1.852	0.065	*
Observations	217				

*p<0.1; **p<0.05; ***p<0.01. Robust SEs in parentheses.

C.2 Regression Diagnostics

C.2.1 Multicollinearity Assessment (VIF)

The Variance Inflation Factor (VIF) was calculated to assess the correlation between independent variables. As shown in Table C.2, all VIF values fall below the critical threshold of 5, confirming that multicollinearity does not bias the coefficient estimates.

Table C.2: Variance Inflation Factor (VIF) Results

Variable	**VIF**	**Tolerance (1/VIF)**
N Capability	4.560	0.219
F Capability	3.671	0.272
H Capability	2.422	0.413
GDP per capita (10k)	1.418	0.705
Pop Density	1.203	0.831
Nuts Dummy	1.177	0.850
Mean VIF	**2.408**	

C.2.2 Heteroskedasticity Test (Breusch-Pagan)

The Breusch-Pagan test checks the null hypothesis of homoskedasticity (constant variance). As shown in Table C.3, the test rejects the null hypothesis for both the linear and log-transformed specifications ($p < 0.01$). This confirms the presence of heteroskedasticity.

Table C.3: Breusch-Pagan Test for Heteroskedasticity

Model Specification	**BP Statistic (χ^2)**	**df**	**p-value**
Linear Model (Model 1)	36.789	6	< 0.001
Log-Transformed Model (Model 5)	20.558	6	0.002

H_0: Homoskedasticity. Rejection ($p < 0.05$) implies heteroskedasticity.

Chapter D

Appendix D: Regional Rankings

The following figure presents the ranking of the top 100 NUTS regions by Deep Tech Venture Density.

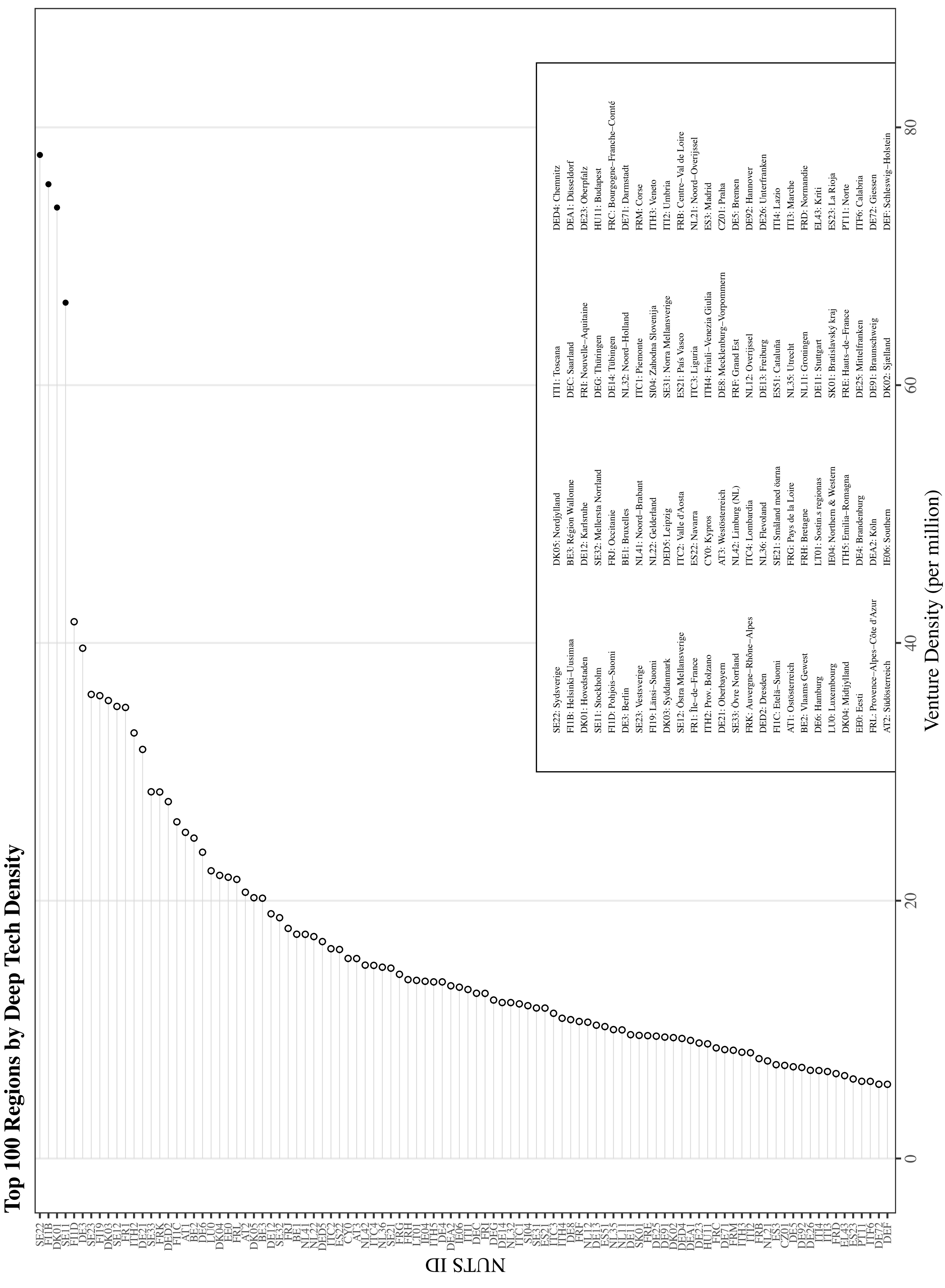

Figure D.1: **Top 100 Regions by Deep Tech Density.** The ranking illustrates the extreme skewness of the dependent variable

Chapter E

Appendix E: Spatial Distribution Map

The following figure visualizes the geographic concentration of entrepreneurial activity across the 217 regions.

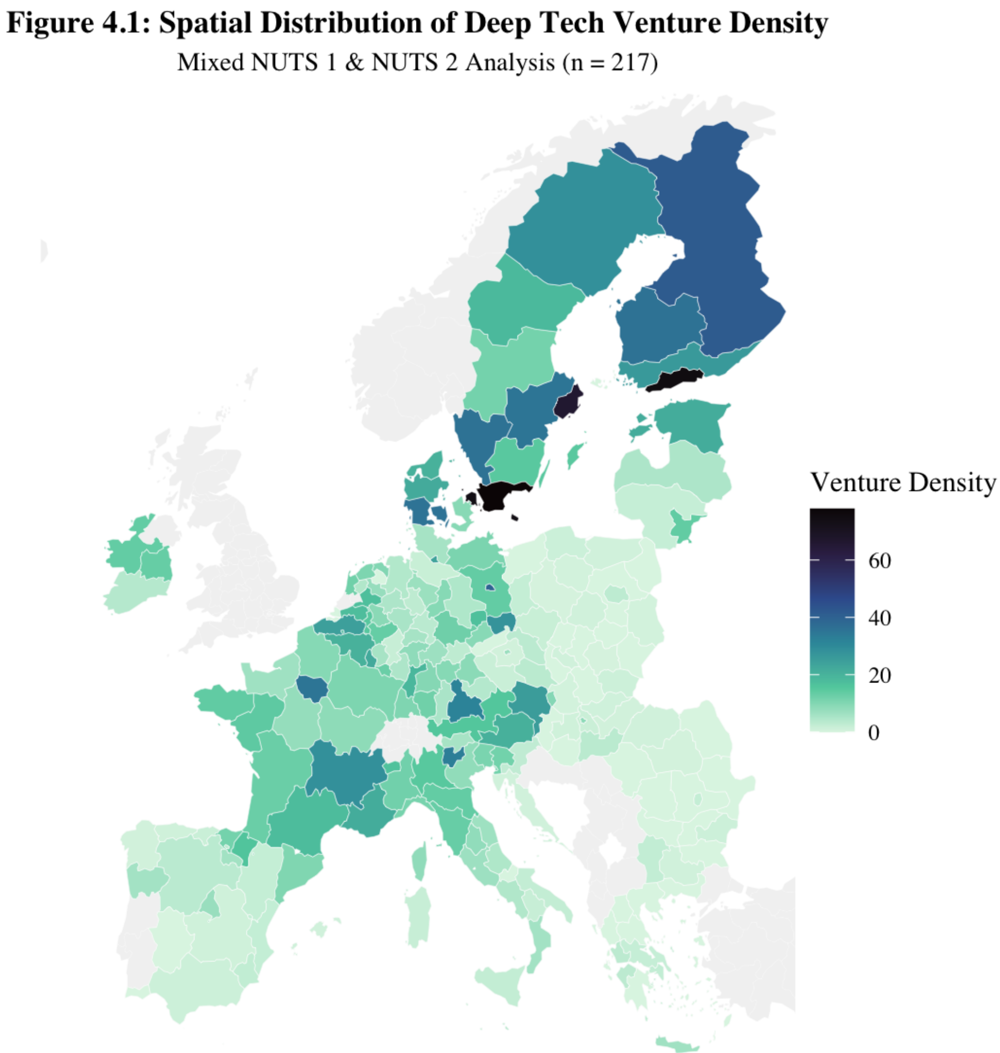

Figure E.1: **Spatial Distribution of Deep Tech Venture Density.** Darker areas indicate higher density "Super-Hubs" (e.g., Stockholm, Helsinki), while lighter areas indicate lower activity, visually confirming the skewed distribution.