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Master's Thesis in Innovation

Network solutions to sustainability problems:

Relationships between connections to a multi-scalar knowledge network and regional sustainability performance

Nettverksløsninger på bærekraftproblemer:

Relasjoner mellom forbindelser til et multiskalart kunnskapsnettverk og regional bærekraftevne

Master's Degree in Innovation

INN3031

2023

Contents

Abbreviations:

DKB = Differentiated knowledge bases

EEA = European Economic Area

EFTA = European Free Trade Association

EIS = European Innovation Scoreboard

EU = European Union

FPs = Framework Programmes

NUTS = Nomenclature of Territorial Units for Statistics

RIS = Regional Innovation Systems

RISB = Regional Innovation Scoreboard (RISB)

SMEs = Small and medium-sized enterprises

Preface & Acknowledgements

This thesis is a product of the authors shared interest in statistical analyses, environmental challenges, innovation, and knowledge networks. Over the past two years, both authors have learned a lot. We have both gained an increased interest in systems of innovation and how the interaction between different actors can contribute to improve or support innovation processes. After discussing which approach we wanted to use for our thesis, we realized that we, in line with innovation theory, could combine our resources to reach further together. By combining our shared interest for quantitative research methods, environmental challenges, and systems of innovation, we reached an idea and understanding of how we could approach this thesis together. The following thesis is a culmination of hundreds of hours spent reading articles, conducting analyses, reflecting on ideas and discussing challenges.

First and foremost, we would like to sincerely thank our supervisor and associate professor Giuseppe Calignano. Your guidance, feedback, patience, and interest in our work throughout this project has been immeasurable. Your interest in our thesis, and the time you have spent assisting us in our work has been key for our ability to submit a thesis we are both proud of. We are very thankful for all you have done for us.

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Furthermore, we would like to thank our fellow students for the support, feedback, suggestions, and a good learning environment throughout the last two years. Because of all of you, spending long days studying and writing has been an enjoyable experience.

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- *Janse Tomas Bergersen & Odin Opsal Grytli, Inland University, Spring 2023*

Abstract

Reaching the EU goal of carbon neutrality by 2050 will require advancements in regional sustainability performance and in energy innovation, production and consumption. This thesis examines how network effects can contribute to these advancements by investigating the relationship between connections to a multi-scalar knowledge network and regional sustainability performance. This was achieved through the use of network data based on the Horizon 2020 (2014-2020 period) Energy Programmes and data on regional innovation performance from the Regional Innovation Scoreboard 2021. By combining econometrics and social network analysis, our empirical results shows that actual positioning in the in the core of a knowledge network is related to gradual increases in regional sustainability performance through reductions in PM2.5 air emissions. Furthermore, our results indicate that peripheral regions might potentially be able to strengthen their sustainability performance by utilizing network effects through key positioning in the network, thereby bypassing the need for an actual positioning in the core network. Based on these results, we argue that local and global policymakers in the EU should make increasing efforts to include peripheral and struggling regions in the EU framework programmes.

Sammendrag

Å oppfylle EUs mål om karbonnøytralitet innen 2050 vil kreve forbedring i regional bærekraftevne og i energiinnovasjon, produksjon og forbruk. Denne avhandlingen undersøker hvordan nettverkseffekter kan bidra til denne utviklingen ved å undersøke forholdet mellom forbindelser til et multiskalart kunnskapsnettverk og regional bærekraftevne. Dette ble oppnådd gjennom bruk av nettverksdata basert på Horizon 2020 (2014-2020 perioden) sine energiprosjekter og data på regional innovasjonsevne fra Regional Innovation Scoreboard 2021. Ved å kombinere økonometri og sosial nettverks analyse viser våre resultater at reell posisjonering i nettverkskjernen er relatert til en gradvis økning i regional bærekraftevne gjennom reduksjoner i PM2.5 utslipp. Videre indikerer resultatene våre at perifere regioner potensielt kan styrke deres bærekraftevne ved å utnytte nettverkseffektene gjennom nøkkelposisjonering i kunnskapsnettverket, og dermed omgå behovet for reell posisjonering i nettverkskjernen. Baser på disse resultatene argumenterer vi for at lokale og globale beslutningstakere i EU bør gjøre en økt innsats for å inkludere perifere og vanskeligstilte regioner i EUs rammeprogrammer.

1. Introduction

Reaching the EU goal of carbon neutrality by 2050 will require advancements in regional sustainability performance and in energy innovation, production and consumption (International Energy Agency, 2021, p. 184; European Commission n.d.[b]). This study will examine how regional connections to a multi-scalar knowledge network can contribute to these advancements.

1.1 Background

Considering the European Green Deal, 2030 and 2050 emission goals, and the need for regions and industries to transition towards more sustainable or "green" alternatives, some regions are better equipped for transition than others. Reaching these goals will, in many cases, demand great industrial adjustments across both state and regional borders. Regional actors, agencies, and organizations, which through their linkages make up the Regional Innovation System (RIS) (Asheim et al., 2019, p. 8), are likely dependent on collaboration and co-creation of both knowledge, processes, and technology to be able to align their industrial activities with these goals. According to Chen & Hassink (2020, p. 2490) knowledge is crucial for a region's ability to develop new industrial paths. Different types of RIS can differ vastly in their innovation capabilities in this respect (i.e., ability to facilitate new or altered development paths).

Modest and moderate regions, which have fewer inter-regional actors, agencies, and organizations, are typically at increased risk of path dependency (Asheim et al., 2019, p. 44-45). This could potentially prove to be a challenge in the context of EUs green restructuring goals since new industrial path development will likely be a necessity for achieving this. Modest regions are furthermore often characterized by a lack of the external knowledge networks connections necessary for preventing path dependency (Asheim et al., 2019, p. 44-51).

According to the International Energy Agency (2021, p. 184), reaching the goal of carbon neutrality by 2050 will not be possible without a major acceleration in clean energy innovation. Energy technology and research and development (R&D) efforts are knowledge intensive activities, which implies a need for relevant, scientific knowledge to be made available. These types of innovations, also known as "Green Innovations", relate to innovations which have a positive or less negative influence on the environment compared to a region's earlier products or processes. The environmental advantages can be the main purpose of the innovation, or a byproduct of other characteristics or purposes of the innovation. Green innovations are defined as “The development of new knowledge which is implemented into a new product, process or service which generates profit while simultaneously reducing the total environmental impact in one or more phases of the product, process or services life course” (Arnekleiv & Larssæther, 2004; Aasen & Amundsen, 2015, p. 43: Our translations). Because of this we were interested in studying the effects participation in a pan-European multi-scalar knowledge network has on sustainability performance at the regional level.

The European Green Deal, which was launched in 2019 is a set of policy initiatives meant to set Europe on the right path towards a green transition and ultimately reach carbon neutrality by 2050 (European Council, 2022). These initiatives cover the topics climate, environment, energy, transport and more, who are all interlinked. Steps have been taken by the European Council to make the Green Deal a legal obligation for member states to work towards carbon neutrality, firstly this relates to cutting emissions by 55% by 2030 compared to emission levels from 1990 (European Council, 2022).

These are ambitious goals, and like we mentioned there are challenges and obstacles in the way that need to be tackled. So, what does the EU do to assist countries and regions in meeting these goals? Among the initiatives we find a research and innovation collaboration called Horizon Europe. Due to the time limitations of this thesis, we used data from energy projects from the previous iteration, called Horizon 2020 (H2020) which happened in the period 2014-2020. The H2020 Energy projects were designed to support the transition to a reliable, sustainable, and competitive energy system (Calignano & Trippl, 2020, p. 3).

We chose to study H2020 energy projects because of the previously mentioned need for major acceleration in clean energy technology as that is one of the main priorities of this part of the H2020 framework programmes. Horizon 2020 Energy projects consisted of 230 different energy projects conducted during the 2014-2020 period.

Why participation in H2020 energy projects?

Considering the previously discussed EU goals for reduction in emissions, and carbon neutrality, many regions lack the necessary resources and competencies to develop new, and more environmentally sustainable industrial paths. Many, if not most of the relevant EU-regions lack the necessary resources in their region and are thus forced to look elsewhere. Considering that the H2020 energy programmes relate to more energy-efficient technologies and solutions and the transition to a "greener" energy infrastructure we deem it as a highly relevant knowledge network for our thesis.

1.2 Purpose and research question

Based on the points discussed above, this paper seeks to identify which factors are crucial for strengthening the sustainability performance of EU regions. This paper seeks to identify these factors by examining connections between regional sustainability performance, and 1) connections to a multi-scalar knowledge network, 2) regional socio-economic, geographical and innovation characteristics. The specific research question for this paper is therefore:

RQ1: *«How can connections to multi-scalar knowledge networks explain variations in regional sustainability performance?»*

> RQ1.1: *«How does regional socio-economic, geographical and innovation characteristics contribute to this?»*

2. Theoretical framework

2.1. Innovation and Green/sustainable Innovation

The term innovation has over time had many definitions, as well as many branching variations (See Taylor, 2017). Innovation is in essence the creation of "new and useful" through combinations of different, already existing resources such as knowledge, materials, and procedures. The term innovation has undergone many reiterations over the years. In 1934, Joseph Schumpeter defined innovation as "new combinations" of new or existing knowledge, resources, equipment, and other factors. Some authors and researchers of innovation say innovation is viewed as a collective process (See Aasen & Amundsen, 2011; 2015) where two or more actors combine their resources to co-create something with a degree of novelty (newness, whether it is to the world, a country, region, firms, or group) (Aasen & Amundsen, 2011). Aasen & Amundsen (2015, p. 18: Our translation) views innovation as a kind of "new practice that is created through collective effort between many actors.". We argue that innovation is a collective process because the knowledge resources applied in innovative effort rarely are produced by the same people that apply them, this doesn't necessarily imply that innovation can't happen alone, but is likely to be a product of cooperation, whether it is through development of theory, technology, or systems etc. Aasen & Amundsen point out that the given collective process is "innovation" regardless of whether the effect is positive or negative. In addition to this Crossan & Apaydin (2010, p. 1155) argue that innovation is not only the process of collaboration and co-creation but also the product the work results in. While there are a wide variety of definitions of the term innovation, there are some common characteristics.

1. Innovation can be viewed as both the process and the product.
2. Innovation is about creating something new (degree of novelty).
3. Lastly, innovation is for something, it needs to have a purpose. Meaning innovation effort must seek to solve a problem or overcome an obstacle.

Furthermore, Innovation has different sub-classifications that are often used to discuss specific effects or goals of innovation effort. For this thesis we mainly focus on innovation that has a positive, or less negative effect on environmental factors and sustainability in general. Terms like eco-innovation, green innovation, sustainable innovation, and environmental innovation are commonly used as synonyms in research papers and innovation literature (Leal-Millán et al., 2017). While these terms are sometimes used as substitutes for one another they carry slight variations in meaning.

Green innovation according to Leal-Millán et al. (2017) is defined as such; “Green innovation comprises all type of innovation that contribute to the creation of key products, services or processes to reduce the harm, impact and deterioration of the environment at the same time that optimizes the use of natural resources”.

Environmental innovation can be defined as “a specific form of innovation aiming at reducing the impact of products and production processes on the natural environment” (Ozusaglam, 2012, p. 16). While the definitions of green-, and environmental innovation are similar they do not include other factors that are central in building a sustainable future. This is where the definition of sustainable innovation comes in, as it also includes economic and social factors as well as the environmental. Sustainable innovation is defined as:

“Innovation in which the renewal or improvement of products, services etc. [..] not only delivers an improved economic performance, but also an enhanced environmental and social performance, both in the short and long term have the capacity to generate positive social and environmental impacts” (Bos-Brouwers, 2010, p. 422; as quoted in Cillo et al., 2019, p. 1013).

This definition will be the basis for how and what we view as innovation. Furthermore, in relation to our research question, we are mainly interested in the knowledge resources and how organizations and regions source their knowledge to be better equipped for sustainable innovation efforts. With this in mind it seems logical to first understand how regions and regional actors can access knowledge both from intra- and extra-regional sources such as knowledge networks.

2.2. Multi-scalar knowledge networks and knowledge sourcing

A knowledge network involves a given number of resources and actors who are able to obtain, share and create new knowledge through cooperation, with the goal of value creation (Du Preez et al., 2008, p. 159). According to Creech & Willard (2001, p. 27) there are several reasons why actors (regions, sectors, organizations, etc.) should prioritize prolonged efforts into knowledge networks. Investing in knowledge networks enables regions to learn improved practices from each other, and one can thereby use the past experiences of external actors when deciding which innovations will further sustainability, thus saving time and resources. Furthermore, one can use external knowledge to eliminate knowledge gaps which would otherwise hinder or obstruct sustainable policies. Likewise, this could ease the region's efforts to eliminate current inadequate policies or implemented innovations.

One way both regions and individual organizations strengthen their innovation potential and performance is by engaging in knowledge networks (Wanzenböck et al., 2015, p. 1686). Previous studies on knowledge networks and innovation performance have shown that organizations can greatly benefit from the knowledge influx that networks offer in their exploration efforts, especially if the collaborating organizations engage in related fields (Guan & Liu, 2016, p. 108). Especially knowledge intensive industries have been shown to greatly benefit from cooperation in their innovation efforts (Wal et al., 2020).

Furthermore, network centrality has been identified as especially important in connection with innovation performance. By being centrally situated within a knowledge network, firms, organizations, and regions gain more potential collaborating actors with which they can exchange knowledge. This enables the acquisition of the knowledge capital one lacks to enhance innovation performance (Wang et al., 2018, p. 230). Knowledge network theory could therefore arguably prove useful in explaining relationships between a region’s connection and role within a knowledge network and the regional sustainability performance.

When a region is in need of new knowledge, it can opt to look internally or externally. Multi-scalar knowledge sourcing is a concept that implies that knowledge acquisition can happen in three ways (from a regional perspective). Knowledge can flow to the region through the arrival of extra-regional organizational or individual actors (Chen & Hassink, 2022, p. 2492). Relocating an R&D organization from one region to another will result in that organization's knowledge being situated in the new region, which can be beneficial for other actors in that region. Knowledge can also be transferred through intra-regional linkages, although the helpfulness of intra-regional knowledge can arguably be limited in attempts to create new industrial paths. Lastly, and perhaps most importantly, new knowledge can be accessed through extra-regional knowledge linkages, meaning knowledge flows from outside the region. Extra-regional knowledge links can be both formal and informal. Formal linkages are typically contractual collaboration between organizations or R&D institutions, by licensing use of patented technology to other actors, or through research collaboration such as R&D activities, alliances, and epistemic communities (Chen & Hassink, 2020, p. 2492). Multi-scalar knowledge networks can therefore be understood as knowledge networks that both consider inter-regional and extra-regional knowledge resource alternatives when attempting to gather new knowledge in their region.

While knowledge can be gathered from many different sources, the type of knowledge also matters. Knowledge can generally be divided into two groups. Firstly, we have tacit knowledge which is embodied/internalized and often achieved through experience and interaction with "something" (system, product, processes etc.) and is difficult to transfer. One reason for this is that this kind of knowledge accumulation often is dependent on the situation the knowledge was gained in (Asheim et al., 2019, p. 38). Secondly, we have explicit knowledge. Explicit knowledge is written down or saved in some way and is therefore easily transferrable compared to embodied, tacit knowledge because it is not necessarily context dependent in the same way. This way of understanding knowledge is a good starting point but becomes somewhat rudimentary when trying to understand the complexity of knowledge creation, learning and innovation (Asheim et al., 2019, p. 38).

Researchers use the concept of differentiated knowledge bases (DKB) to make distinctions between three different types of knowledge bases that co-exist within a firm or region (Chen & Hassink, 2020, p. 2491). These knowledge bases are called synthetic, analytical, and symbolic knowledge bases. According to Asheim et al. (2019, p. 38) "analytical knowledge refers to economic activities where scientific knowledge based on formal models and codification is highly important". Knowledge inputs and outputs are usually codified (typically using industry/field specific language to accurately communicate findings, results etc.) Because of this, workers in sectors that deal mostly with analytical knowledge needs some form of research experience or higher education to understand and participate in the process. The analytic knowledge base produces knowledge through scientific discovery and technological invention/application. Due to the analytic knowledge base consisting of explicit and codified knowledge, it may easily be transferred on the global scale through various scientific communities and through industry-university collaborations (Chen & Hassink, 2020, p. 2492).

“Synthetic knowledge bases refer to economic activities where innovation takes place mainly through the application or novel combinations of existing knowledge” (Asheim et al., 2019, p. 40). Synthetic knowledge is often used to solve specific problems that emerge from the interaction between actors, firms, customers, etc. Unlike the analytic knowledge base, synthetic knowledge bases rely on a combination of tacit and explicit knowledge. This can be due to the need to solve specific problems that are uncovered through interaction with other actors such as customers, collaborators, competitors. Compared to analytic knowledge, synthetic knowledge is more reliant on know-how and practical skills in combination with scientific knowledge to meet needs and solve problems. This type of knowledge most often results in incremental innovations and process optimalization by tweaking current products and services to customer needs (Asheim et al., 2019, p. 38-41).
Considering transferability, synthetic knowledge is more difficult to transfer on a global scale. It is however possible to transfer, but this might require individuals to travel “with” the knowledge to both share the knowledge and the context in which it was acquired (Chen & Hassink, 2020, p. 2492).

Lastly symbolic knowledge bases are related to the creation of meaning and desire as well as aesthetic attributes of the products such as designs, images, and symbols, and to their economic use. According to Asheim et al. (2019, p. 42) symbolic knowledge is characterized by tacit knowledge and this knowledge is often highly context specific. Since tacit knowledge is hard to transfer and often hard to transfer over geographical distances this form of knowledge will likely not be relevant for our analysis. This is because the nature of innovation, networks and RIS all build on the concept of knowledge exchange which indicates that the type of knowledge exchanged in these networks are analytical, explicit knowledge similar to the STI-mode of innovation. This is supported by Wanzenböck et al. (2015, p. 1686) that point out that the European Framework Programmes are key STI policy instruments in R&D projects and creating a pan-European knowledge network.

Considering the importance of knowledge in innovation processes in combination with the need for specific types of knowledge, we were interested in understanding how participation in large scale knowledge networks and potential access to relevant knowledge resources would contribute to regional sustainability performance through increased ability for regional industrial path upgrading, path diversification, path importation and new path creation.

2.3. Regional Innovation and different types of Regional Innovation Systems (RIS)

In this thesis we apply the theory of RIS to study how the European regions sustainability performance is affected by connections to a multi-scalar knowledge network.

The theory of regional innovation systems (RIS) is based on "the central idea that a region's innovative performance depends on the innovative capabilities of firms and research institutions, and how they interact with each other and public institutions" (Doloreux, 2002, p. 243). Innovation systems are generally made up of linkages between different actors, agencies and organizations that contribute to promoting innovation in their region (Asheim et al., 2019, p. 8). One typically differentiates between three main types of RIS, based on their potential for innovation, interactive learning, and entrepreneurship. The three main types of RIS are thick and diversified RIS, thick and specialized RIS, and thin RIS (Asheim et al., 2019, p. 44-45). RIS mainly consists of two subsystems. These are exploration units (also called knowledge producing units) and exploitation units which cooperate over time (Asheim et al., 2019, p. 8). In other words, a RIS is made up of lasting beneficial cooperation between the exploration of new knowledge and the exploitation of this knowledge in innovative work.

Different types of RIS create varied potential for regional innovation. Furthermore, different types of RIS differ in their capacity for new regional industrial path development and risks of path dependency. New regional industrial path development refers to the development of new economic activities in a given region. Path development is in essence related to a region's capacity, or lack of capacity for innovation within existing or new types of industry (Asheim et al., 2019, p. 43-47). This process can be understood as an attempt to develop and anchor necessary resources. Accumulating new and relevant knowledge is arguably the most important aspect of this process. Knowledge creation or other ways to attain new knowledge (I.e., diffusion, formal and informal linkages) is highly necessary to feasibly be able to develop new, upgraded, or different industrial paths within a region. The ability to restructure or change regional industrial paths also varies depending on what type of RIS is present (Trippl et al., 2020, p. 191).

Thick and diversified RIS are typically characterized by a strong or leading capacity for innovation in both established (related) and completely new (unrelated) industries. These regions typically contain varied industrial organizations, as well as the presence of supporting organizations which facilitate innovation across different sectors (Chen & Hassink, 2020, p. 2491). The knowledge networks present within these regions are often varied and geographically open (Asheim et al., 2019, p. 44-45). Based on these characteristics, one could argue that thick and diversified regions possess a strong capacity for new path development. Thick and diversified RIS (I.e., Strong innovators and Innovation leaders) often facilitate both related and unrelated path diversification, as well as new path development.

Thick and specialized RIS are typically characterized by a moderate innovation capacity. These regions typically contain strong industry, but the present industry is often concentrated on one or a few sectors. The existing support organizations and knowledge bases are often heavily tailored to the existing industry in the region, leading to a highly specialized industrial sector (Chen & Hassink, 2020, p. 2491). Likewise, the knowledge networks in these regions are closed off geographically and specialized to that specific regions' industrial structure. In other words, these regions have a strong potential for innovation within the established sectors, but the capacity for path development in new sectors will likely be limited. The risk of path dependence or lock-in will likely be greater in these regions than in thick and diversified regions (Asheim et al., 2019, p. 44-45). Thick and specialized RIS (I.e., moderate innovators) contain some potential for related path development. These regions often rely on path upgrading and extension as viable alternatives. Thin RIS (I.e., emerging/modest innovators) typically lack the capabilities necessary for path- diversification or development, and often must rely on path upgrading, extension and importation (Asheim et al., 2019, p. 50).

Thin RIS arguably overlaps with the "Emerging/modest innovators" from the
RISB. These regions typically contain a few insufficiently developed industrial clusters or none at all. Thin RIS regions typically suffer from a lack of local actors and a lack of knowledge flow. Thin RIS often consists of a few weak firms or non-firm actors. Thin RIS regions thus tend to lack the necessary number of actors in any specific industry (Chen & Hassink, 2020, p. 2491). Furthermore, there are often few knowledge bases and supporting organizations present in these regions. The risk of path dependence, lock-in and path exhaustion is often greatest in these regions, and they are often dependent on external actors to facilitate new knowledge development (Asheim et al., 2019, p. 44-45). Thin RIS are most commonly found/associated with peripheral/rural geographical areas.

According to Calignano & Trippl (2020, p. 14) innovation literature suggests that more innovative regions are clearly associated with stronger RIS. Stronger RIS are typically characterized by more actors and research institutions as well as a more heterogeneous knowledge base. Based on this we chose to apply RISB grouping to approximately identify whether a regional innovation system can be classified as thin, thick and specialized or thick and diversified. The reason for this is so that we can consider how differently equipped RIS can benefit from participating in H2020 Energy.

2.4. New regional industrial path development

Four types of new regional industrial path development have been identified by scholars, namely path upgrading, path diversification, path importation and new path creation (Grillitsch et al., 2018, p. 266). Path upgrading refers to developing a new industrial path within an already established industry. This is attainable by adding new knowledge to a region's existing industry. Path diversification means developing a new industry by combining knowledge already in the region with new, extra-regional knowledge. The main difference between path upgrading and diversification is that path diversification creates economic activities in a new industry while path upgrading stays in the same industry (Chen & Hassink, 2020, p. 2491).

While path upgrading and diversification relies on already existing knowledge in the region, path importation and new path creation is dependent on extra-regional knowledge. When a region creates new industrial activities based on knowledge that is almost entirely from outside the region it is called path importation. In other words, the given region is inspired by another and import knowledge from that or similar regions to engage in similar economic activities. Lastly, new path creation relates to commercialization of new-to-world knowledge to create a completely new regional industrial path. The main difference between path importation and new path creation is the degree of novelty. Path importation uses new-to-region knowledge while new path creation relies on new-to-world knowledge (Chen & Hassink, 2020, p. 2491).

Different types of RIS regions have different capacities for path development as well as risks of path dependence (Asheim et al., 2019). It is not unlikely that several regions will be dependent on new industrial- and knowledge development (i.e., new path development) in order to reach EU's climate goal of carbon neutrality. This theory could therefore prove useful in explaining the connections between different types of RIS, as well as specific types of innovation, and sustainable innovation capabilities.

2.5. Sustainability

In the context of innovation, sustainability is often used to describe a firm or organization's ability to adapt and survive in a competitive environment. Different bodies of government expect firms and enterprises to take (part of the) responsibility for economic, environmental, and social sustainability in the areas they operate (Aasen & Amundsen, 2011, p. 248: Our translation). As mentioned, sustainability is regarded as a combination of both economic, social, and environmental factors with the end goal of "Meeting the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland & Dahl, 1987, p. 18: Our translation). Economic sustainability relates to a firm, region, or organization's ability to maintain economic growth (Aasen & Amundsen, 2011, p. 248: Our translation). An example would be the introduction of new products or technology that succeeds or fails in earning back the resources used in development through sales. Environmental sustainability is more focused on the consumption of natural resources and natural ecosystem's ability to survive and maintain themselves. Lastly, social sustainability is related to social factors such as healthcare, welfare, social security, and a population's standard of living.

In this thesis the sustainability concept is meant to be contextual. When studying the effects of knowledge network participation on sustainability performance we argue that understanding sustainability as the combination of economic, social, and environmental sustainability is important.

3. Deliminations

In our thesis we chose to limit the knowledge network approach to only including explicit knowledge. “Knowledge” in our thesis mainly relates to the STI mode of knowledge (Jensen et al., 2007). While we do not discount the possible contribution of DUI knowledge for strengthening regional sustainability performance, this is outside the scope of our thesis. Since we are focusing on general tendencies across the EU, we deemed it most appropriate to focus on types of knowledge which is easily transferable regardless of physical proximity.

Another reason we considered the FPs to largely depend on scientific knowledge is found in the description of the Energy projects from H2020. H2020 designed the Energy challenge to support transition to a reliable, sustainable and competitive energy system (European Commission, n.d.[B]). The effort was divided into seven categories:

1. Reducing energy consumption
2. Low-cost, low-carbon electricity supply
3. Alternative fuels and mobile energy sources
4. A single, smart European electricity grid
5. New knowledge and technologies
6. Robust decision making and public engagement
7. Market uptake of energy and ICT innovation

At least five out of these seven are directly related to development of new and better technological solutions, which supports our assumption that the knowledge shared in the H2020 energy project knowledge-network is based on explicit, codified, scientific knowledge.

Furthermore, our thesis is limited to a knowledge network encompassing EU, EFTA and EEA member regions. While we suspect that the effects of knowledge network participation on air pollution might vary across different geographical locations due to cultural, political and socio-economic differences, we chose to focus on EU regions at the NUTS 2 level because of data availability. Due to time constraints, we deemed it necessary to use existing data to be able to complete our thesis within the given timeframe. While we in this thesis study network participation’s effect on regional sustainability, our primary focus is arguably on environmental sustainability due to our dependent (proxy) variable PM2.5 air emissions being directly related to the latter, as this is argumentatively the most relevant pillar in the context of the European Green Deal (European Council, 2022) and the 2030 & 2050 goals of the EU (European Commission, n.d[.A),] which is the overarching context of our thesis.

4. Method

This thesis focuses on European NUTS 2 regions to investigate the relationship between multi-scalar knowledge networks and regional sustainability performance.

4.1. Procedure

This thesis makes use of multiple quantitative datasets and both traditional statistical analyses and social network analyses.

Firstly, data on innovation indicators was extracted from the 10th edition of The Regional Innovation Scoreboard (RISB). These data are publicly available from the European Commission Publications Office.

Secondly, data on knowledge networks were extracted from a case-by-case matrix on regional participation in the 230 projects from the Horizon Europe 2020 (H2020) energy programs.

The data on RISB indicators and knowledge networks contained scores from a differing number of economical regions. It was therefore decided to limit the analyses sample to regions which are part of the EU, EEA, and EFTA, since the European Green Deal and the 2030 & 2050 emission goals is the context of our thesis. It was decided to include the regions which constitutes the United Kingdom (UK), as the UK's withdrawal from the EU was not finalized until January 2020.

4.1.1. Region inclusion & exclusion criteria

Our inclusion/exclusion process for which European regions to include in our analysis went through several stages (see figure 1). Firstly, our original sample was based upon criteria of data availability. For a region (at NUTS 2 level) to be included, it had to be both included in the regional innovation scoreboard and have participated in the H2020 energy projects. This reduced our sample from 265 to 240 regions.

Secondly, the region had to be part of either EU, EFTA or EEA member states. As previously mentioned, an exception was made for regions belonging to the United Kingdom since a significant portion of our data predates Brexit (finalized January 2020). This further reduced our sample to 236 regions.

Thirdly, regions were excluded based on individual data availability for our dependent variable. Regions which lacked data for 2018 or the 2018-2021 period either completely, or to such a degree that scores were clearly invalid, were excluded. This reduced our sample to 227 regions for our static effects analysis and 226 regions for our dynamic effects analysis.

Lastly, powerful outliers were removed from our sample, which produced a final sample of 217 regions for our static effect analysis and 223 regions for our dynamic effect analysis.

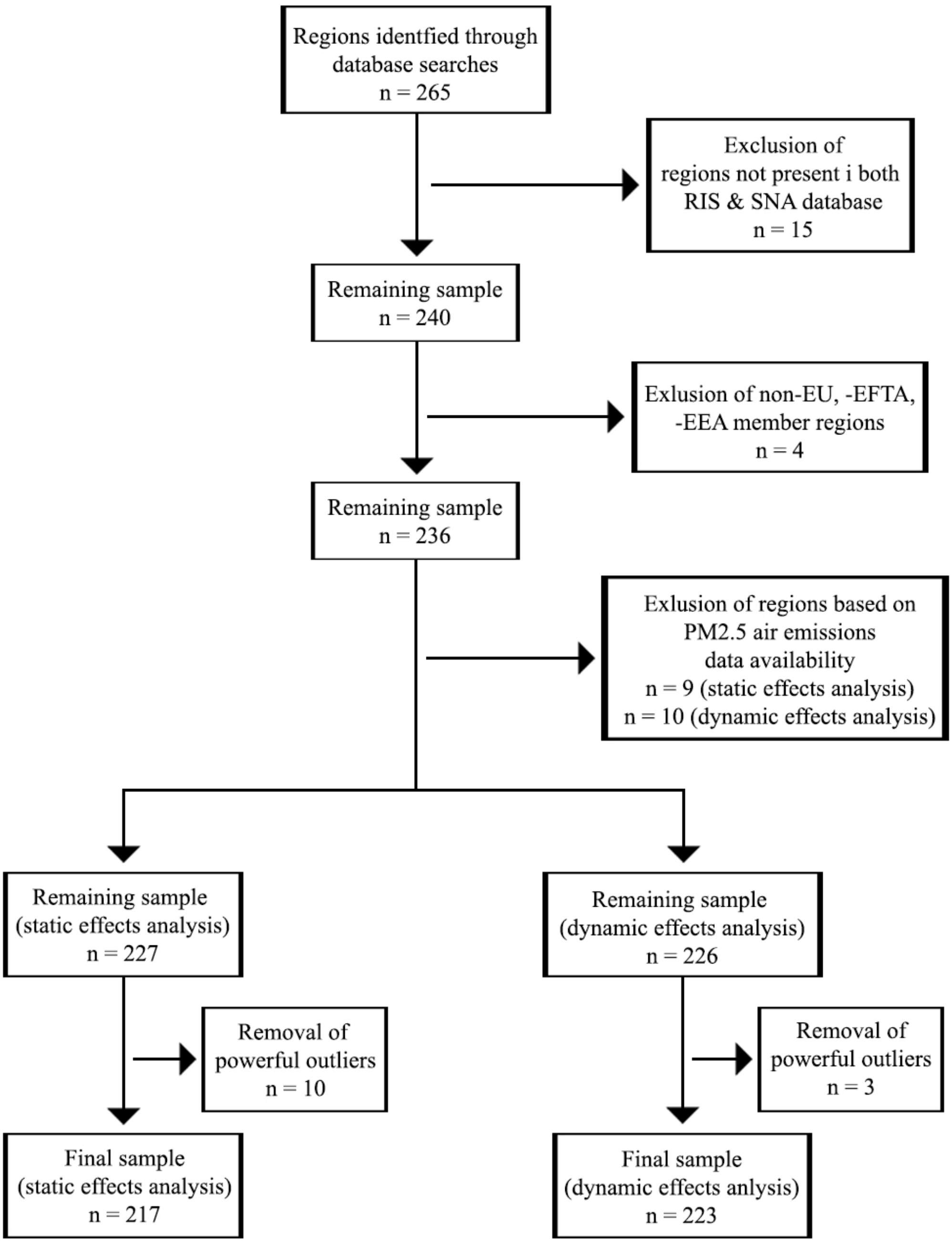

Figure 1. Procedure for exclusion of regions from our sample

4.2. Materials

Regional Innovation Scoreboard Indicators

Both the dependent variable (exposure to PM2.5 air emissions) and the control variables (socio-economic and innovation-characteristics measures), have been created from indicator scores from their respective innovation dimensions from the RISB (see table 1).

Table 1. *Innovation dimensions in the Regional Innovation Scoreboard and their affiliated types of indicators.*

Main indicator type	**Innovation dimension**
Framework conditions	Human resources
	Attractive research systems
	Digitalization
Investments	Finance and support
	Firm investments
	Use of information technologies
Innovation activities	Innovators
	Linkages
	Intellectual assets
Impacts	Employments impacts
	Sales impacts
	Environmental sustainability

An additional economic control variable (GDP) was created from publicly available data on regional GDP from Eurostat.

For the variables pertaining to indicator scores, there were drastic differences in the variables respective range. While some variables had scores ranging from <1-10, other variables had scores ranging from 1-10 000. For this reason, we decided to use normalized scores for these variables to organize the variables into a common scale, ranging from -1 to 1. Normalized data for the static RISB variables is publicly available in the from Eurostat.

Dynamic measures for each of these variables were created in order to examine how changes over time were related to changes in the dependent variable. Dynamic scores were calculated by using the difference between regional scores in 2018 and 2021, resulting in measures of changes over a three-year period.

Furthermore, the 10th ed. Regional Innovation Scoreboard (RISB) contains more indicators than its predecessors, one of which is our dependent variable, "Exposure to fine particulates (PM2.5)". This indicator is one of three indicators on the EIS2021 which constitutes the "Environmental sustainability" dimension, which itself belongs to the "Impacts" main group of indicators. This is the first instance of environmental sustainability measurements within both the EIS and RISB (European Commission, 2021, p. 81). This indicator measures the average exposure levels of PM2.5 for the population of each region. Air pollution in general is harmful for both the environment and humans, but PM2.5 is the most harmful pollutant to human health according to the WHO (European Commission, 2021, p. 88). This indicator is particularly central to this paper because PM2.5 is produced through the usage of fossil fuels. Changes in regional PM2.5 levels therefore function as a satisfactory indication of whether a region is on the path towards carbon neutrality and was therefore deemed to be an appropriate proxy measurement for regional sustainability performance.

Country fixed effects

Country fixed effects were added as a control variable to our static analysis in order to investigate whether our results were robust against the effect of regional geographical placement. This effect was measured by creating binary variables for each country in our sample, where "1" values signified that a region belonged to the respective country and "0" values signified that a region did not belong to the respective country.

Social Network data

The materials for the social network analysis are based on regional (NUTS 2 level) participation data from 230 projects from the Horizon Europe 2020 (H2020) energy programmes, which are available through the CORDIS database. A case-by-case matrix as proposed by Calignano & Trippl (2020, p. 5), where cases represent participating EU regions, form the basis of our network data. The matrix database was created by using a symmetrized overview of the regions in our sample, where values signified how many times two regions had participated in the same H2020 energy project simultaneously. If organizations from two regions had participated in at least one of the H2020 Energy projects simultaneously, then these regions were classified as connected. (Calignano & Trippl, 2020, p. 5). This matrix was then dichotomized which produced a matrix of binary values. "0" values signified that two regions were disconnected, while "1" values signified that the two regions were connected. Centrality measures were used to carry out our social network analysis and to create network variables for our main analyses.

Furthermore, centrality measures (i.e., degree, closeness and eigenvector) were used as the main independent variables for our thesis. Centrality measures, in this context, measures different modes of connections between nodes in the network, with each node corresponding with a given region. Degree centrality is a measurement of each nodes' number of ties to other nodes in the network. Eigenvector measures a given nodes' connection to other nodes of particular influence. Closeness is a measurement of the mean score of the shortest path to every other node in the network for the node in question (Calignano & Trippl, 2020, p. 5).

RISB performance groups

2021 Performance groups from RISB was used as an attribute in our investigative analysis to examine possible relationships between degree centrality scores and RIS. Regions are categorized into one of four performance groups (in ascending order from weakest to strongest; emerging, moderate, strong and innovation leader) based on their overall innovation performance, which is based on their respective scores in each of the innovation dimensions (see table 1) and their associated indicators (European Commission, 2021, p. 6).

In our thesis we chose to categorize regions into three performance groups by grouping the strong and innovation leader regions from RISB into one group. These groups are "modest regions" (emerging innovators from RISB), "moderate regions" (moderate innovators from RISB), and "strong regions" (strong innovators and innovation leaders from RISB).

The argument for this division into three groups is that such a division arguably corresponds satisfactorily with the three main types of regional innovation systems (Asheim et al., 2019, p. 44), with modest regions corresponding with "thin RIS", moderate regions with "thick and specialized RIS" and strong regions with "thick and diversified RIS". The rationale for this decision is that the literature on the potential for path development for each type of RIS (Asheim et al., 2019, p. 43-50), and how different RIS can exploit different knowledge sources for new regional industrial path development (Chen & Hassink, 2022) is well developed. This division thus enables us to make inferences about regional path development potential from our results. For more information about the dependent, independent and control variables, see appendix B.

4.3 Analyses

The analyses in this thesis were carried out using IBM SPSS Statistics version 28, Microsoft Excel and Ucinet 6 for Windows. Ucinet 6 was used to create centrality measurement variables (I.e., our independent variables). Ucinet 6 was further used for social network analyses and to edit matrix data. Visualizations for our investigative analysis were created with the Ucinet 6 add-on “Netdraw”, and SPSS was used to create the descriptive statistics for these visualizations. SPSS was further used for statistical analysis. Excel was used for creating our data sets and for editing them when necessary.

Since the aim of our analyses is to investigate the relationship between multiple independent- and control variables on the dependent variable, it was deemed appropriate to make use of multiple linear regression analysis.

4.4 Methodological approach

In the first step we used social network analyses to carry out centrality measurements of the regions in our network and subsequently created visualizations of our network to investigate the relationship between network centrality and RIS. In the second step we used multiple linear regression analysis to investigate the static effects of connections to a multi-scalar knowledge network and regional air pollution. In the third step we used multiple linear regression analysis to investigate the dynamic effects of connections to a multi-scalar knowledge network and regional sustainability performance, proxied by changes in regional air pollution (see figure 2).

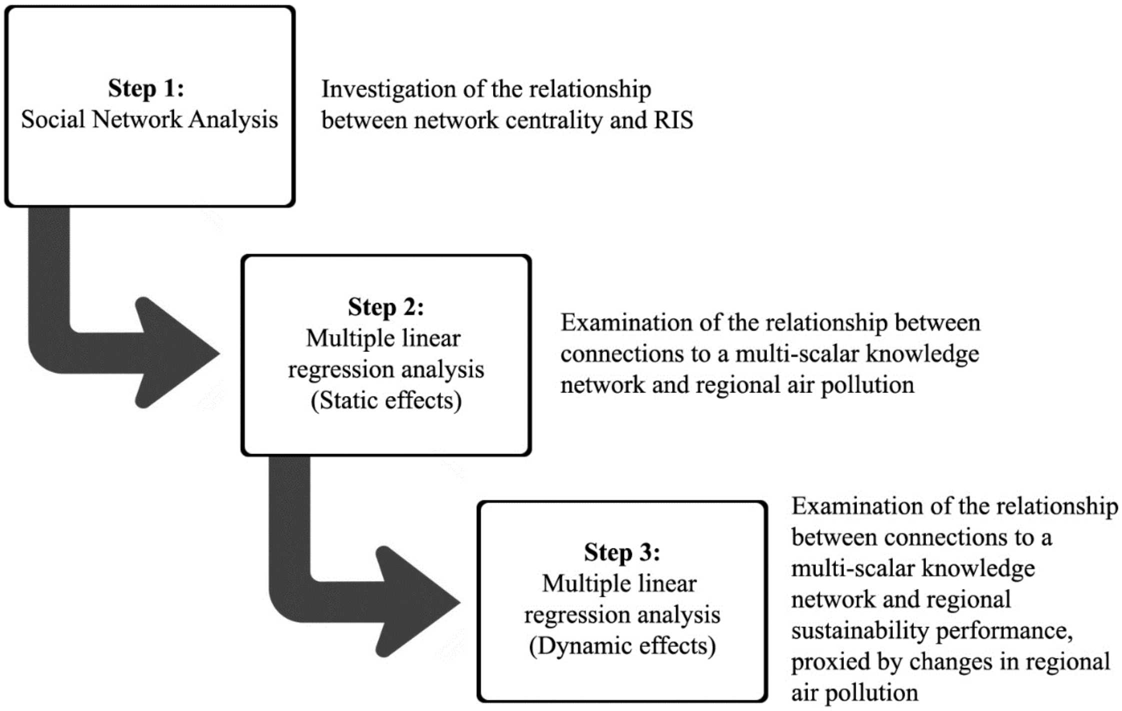

Figure 2. Visual representation of the steps taken in our methodological approach

5. Results

Multiple analyses were carried out to give a thorough examination of our data. Simple social network analyses were used in a preliminary investigative analysis to assess connections between degree centrality (i.e., actual connections in the knowledge network) and type of RIS (see table 2). Netdraw was used to visualize the results (see figure 3). Multiple regressions analysis was used for the main analyses related to the research questions. Both static effects (within a given year) and dynamic effects (changes over time) of regional connections to a multi-scalar knowledge network were examined (see table 4 and 5 respectively).

5.1 Preliminary analysis

Assumptions were checked to assess the appropriateness of using multiple linear regression to analyze the data. Firstly, standardized residual values were inspected to identify potential outliers. Residuals outside the -3 to 3 thresholds were deemed as powerful outliers and removed. Secondly, P-P plots were inspected which indicated a linear relationship between the independent and dependent variables in each model. Thirdly, Q-Q plots were inspected for each variable which indicated that the data satisfied the assumption of multivariate normality. Fourthly, VIF scores were checked for issues with multicollinearity. No such issues were identified. Lastly, scatterplots were inspected which indicated that the data satisfies the assumptions of homoscedasticity.

5.2 Investigative analysis – Degree centrality & RIS

Social network analysis (SNA) was utilized to investigate possible connections between degree centrality scores and RIS. The results seem to indicate a connection between the variables (see figure 3). In general, the core of the network is mainly made up of strong RIS regions (green nodes) and some moderate RIS regions (yellow nodes). The results further indicate a clear relationship between degree centrality and types of RIS, with strong RIS regions having higher centrality degree scores (indicated by node size). The modest RIS regions (red nodes) are mainly situated at the periphery of the network, characterized by low degree centrality scores and few connections to other regions. Furthermore, the thin RIS regions make up the majority of regions which are completely detached from the network (see top left corner of figure 3).

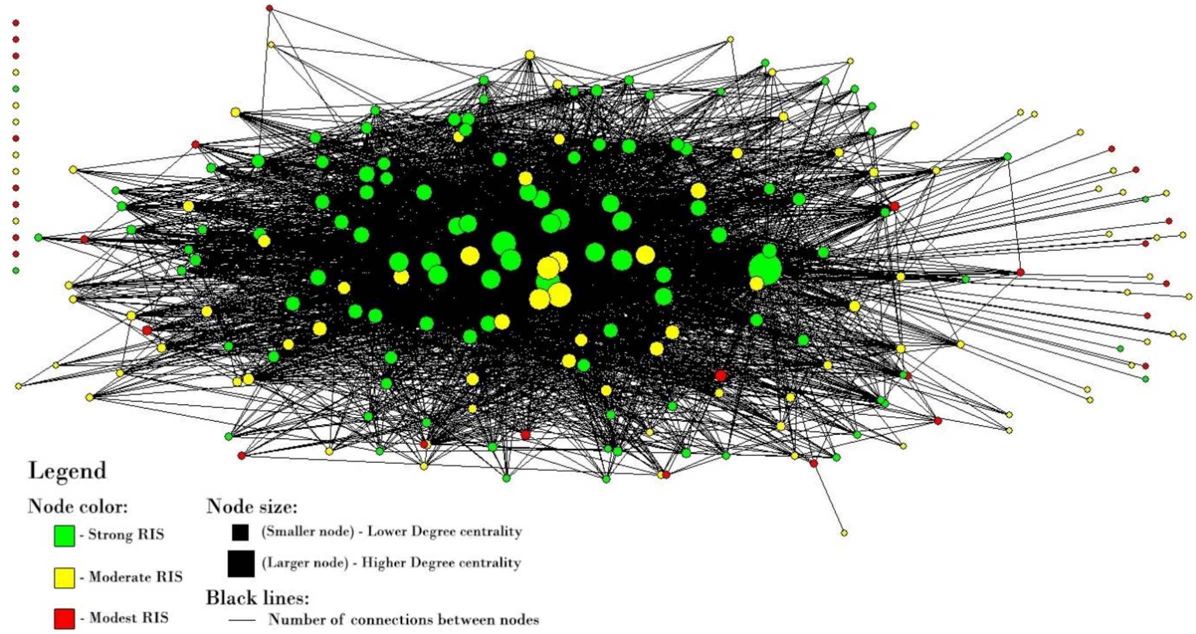

Figure 3: connections between degree centrality scores and RIS

Figure 3b: Strong and moderate regions

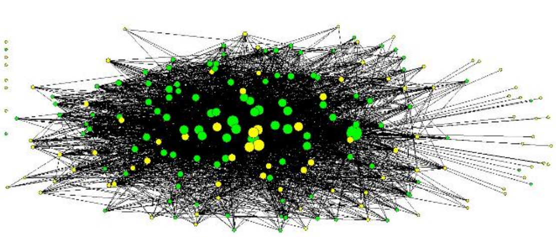

Figure 3c: Moderate and modest regions

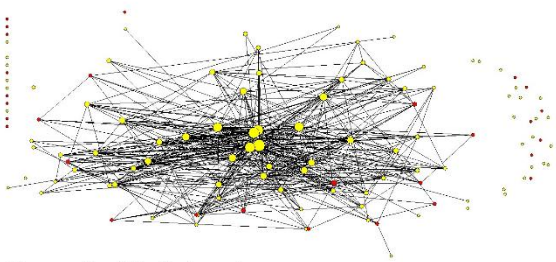

Figure 3d: Strong and modest regions

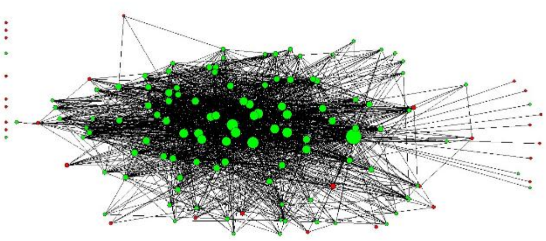

Figure 3e: Modest regions

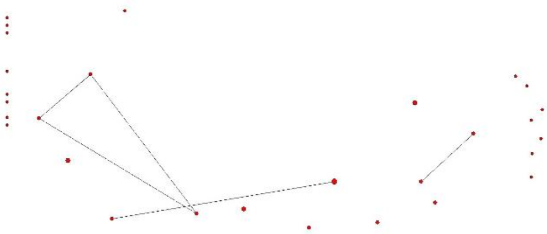

Figure 3f: Moderate regions

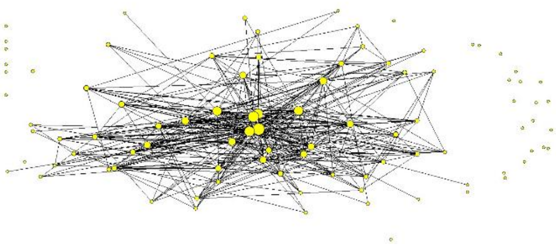

Figure 3g: Strong regions

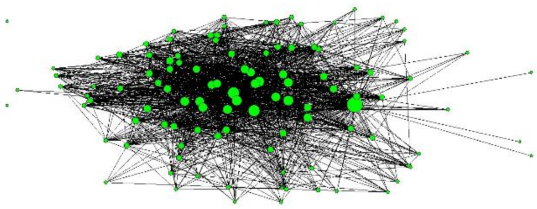

Figure 3b-3g: Further connections between degree centrality and RIS (modest, moderate, and strong regions). Note: Full size versions each figure is available in appendix C.

The results further indicate that strong regions are generally both well connected to each other (see figure 3g) and to moderate and modest regions (figure 3b and 3d respectively). Moderate regions are generally connected to both other moderate regions (see figure 3f) and modest regions (see figure 3c), as long as they are situated at the inner or outer parts of the networks' core. The peripheral moderate and modest regions are however disconnected from the outer and inner core moderate and modest regions (see figure 3c) and are in most cases only connected to strong regions (see figure 3b and 3d). Modest regions show a high prevalence of disconnection to each other and the overall network (see figure 3e). Most of these regions have no connections to other modest regions, and around a quarter of the modest regions are completely detached from the overall network. Very few intra-group connections exist among the modest regions. For further information on the visualization of the investigative analysis, see appendix C.

Further investigations of degree centrality scores grouped by RIS (see table 2) seem to align with our interpretation of the results. Moderate and strong regions have an average of 3,36 and 6,09 times more connections to other regions, respectively, when compared with modest regions. Median scores further illustrate the gap between strong and modest regions. Mean and median scores for strong regions (44,75 and 41,00 respectively) are relatively similar. For modest regions however, the mean score (7,35) is more than seven times that of the median score (1,00). This further illustrates that while a few modest regions are better connected to the overall network, the majority of modest regions have very few connections to other regions. Lastly, the maximum number of connections for any modest region is 32, which is 4,06 times less than moderate regions and 5,88 times less than strong regions. This seems to suggest a reduced connectivity potential for modest regions.

Table 2. *Number of ties per node for each type of RIS*

	Mean	Median	Min	Max
Modest RIS	7,35	1,0	0	32
Moderate RIS	24,68	15,5	0	130
Strong RIS	44,75	41,0	0	188
Total	32,05	23,0	0	188

All in all, the results indicate that core regions are generally characterized by strong RIS with a relatively high presence of both intra- and intergroup connections to other regions. On the other hand, peripheral regions are mostly characterized by either moderate or modest RIS. Modest RIS regions especially, are mainly either situated in the periphery or completely detached from the network, with few or no intra- or intergroup connections to other regions. In essence, it would seem peripheral regions in the network have an increased likelihood of being characterized by modest RIS, with less connectivity potential compared to other regions in the network.

5.3. Main analyses – effects of connections to a multi-scalar network

Two analyses were carried out to assess static and dynamic effects of connections to a multi-scalar knowledge network on regional sustainability performance. Scores from specific years for appropriate variables were utilized to assess the static effects, while changes over a three-year period in the variables were used to assess the dynamic effects, with exceptions for certain control variables (see appendix B). Descriptive statistics for each variable are presented below (see table 3).

Table 3: Descriptive statistics for static & dynamic effects

	N	*M*	*SD*	Min	Max
Static effects					
Degree	220	0,140	0,139	0,000	0,807
Eigenvector	220	0,049	0,044	0,000	0,172
Closeness	220	0,461	0,079	0,200	0,715
Public R&D exp.	220	0,403	0,260	0,000	1,000
Business R&D exp.	220	0,352	0,271	0,000	1,000
SMEs collaborating	220	0,461	0,283	0,000	1,000
GDP	217	0,308	0,182	0,000	1,000
Air emissions (PM2.5)	220	0,549	0,204	0,027	0,969
Dynamic effects					
Degree	223	0,142	0,140	0,000	0,807
Eigenvector	223	0,050	0,044	0,000	0,172
Closeness	223	0,461	0,081	0,200	0,715
Tertiary education	223	0,426	0,082	-,489	0,252
Lifelong learning	223	0,004	0,044	-,127	0,186
Non-R&D innovation expenditure	223	0,012	0,157	-,502	0,629
Innovation expenditure per person	223	0,036	0,073	-,122	0,278
Business process innovations	223	0,119	0,231	-,512	0,570
Knowledge-intensive activities	223	0,018	0,050	-,191	0,196
Air emissions (PM2.5)	223	0,025	0,067	-,126	0,244

Note: Model 1 includes binary variables for country fixed effects (reference country: Germany).

The static effects analysis is mainly concerned with factors that are measured at specific times or less prone to change, and how they might be related to regional pollution for a given year. For this reason, the analysis aims to capture key economic characteristics at the regional level, to determine whether how advanced a region is influences sustainability. Country fixed differences were also used as a control variable in this analysis, as the geographical positioning of regions are constant.

The dynamic effects analysis is conversely concerned with how changes in socio-economic variables and innovation characteristics might be related to changes in regional pollution, and by extension, sustainability potential. For this reason, both control variables and the dependent variable in this analysis measures changes in their respective scores between 2018-2021.

The centrality measures are the main variables of interest in both the static and dynamic approach, as they measure the effect of connections to a multi-scalar knowledge network. These variables were therefore included in both analyses. These measures fall somewhere between that of static and dynamic measures, as they are based upon several years of regional participation in the H2020 framework programmes, specifically the energy projects. Only degree centrality and eigenvector centrality were included in the static analysis since these variables are related to a regions' actual positioning in a knowledge network. Closeness centrality on the other hand is more related to future possibilities for a region through key positioning in the network and was therefore included in the dynamic analysis. The results from both analyses are reported below.

5.3.1 Multiple regression analysis – static effects

Multiple regression analysis was utilized to examine whether there were connections between regional centrality scores, and regional sustainability performance for a given year (2021). Individual analyses were carried out for both centrality measurements (degree centrality and eigenvector centrality) to assess the individual effect of each independent variable, reported as model 1 and 2 respectively. Static scores were further used for each of the remaining control variables.

Table 4: Summary of multiple regression analyses for static effects (N = 217)

	Model 1			Model 2		
	B	*SE B*	β	*B*	*SE B*	β
Degree	-,148	,050	-,102**			
Eigenvector				-,531	,163	-,115**
Public R&D exp.	,008	,028	,010	,011	,028	,014
Business R&D exp.	-,006	,029	-,007	-,003	,029	-,004
SMEs collaborating	-,096	,044	-,133*	-,092	,044	-,127*
GDP	-,024	,043	-,021	-,021	,043	-,019
Country fixed effects		YES			YES	

Note: *p<,05, **p<,01, ***P<,001, Reference country for country fixed effects: Germany

In the first place, the overall regression was statistically significant for both Model 1 (R^2 = 0.90, F(29, 187) = 57.94, *p* = <.001), and Model 2 (R^2 = 0.90, F(29, 187) = 58.55, *p* = <.001).

Centrality measures were negatively related to PM2.5 air emissions in both models, which indicates that in both instances, a higher centrality score corresponds with lower air pollution scores.

Interestingly, among the remaining control variables, SMEs collaborating (Innovative SMEs collaborating with others) was the only statistically significant variable across both models. This is seemingly in line with the overall results, as this is the only economic variable which incorporates a relational approach, which in turn seems to strengthen the assumption of a connection between knowledge sharing and sustainability performance.

Surprisingly, while not statistically significant, GDP was negatively related to PM2.5 air emissions, which would indicate that PM2.5 air emissions would be lower in richer regions. While one perhaps would intuitively assume that richer regions would be characterized by cities and metropolitans (typically strong RIS) which would be subject to more air emissions, one could perhaps surmise that these regions would perhaps also be better equipped to deal with such issues through new path development.

In any case, the static results indicate that stronger connections to a multi-scalar knowledge network are related to lower regional PM2.5 air emissions. This relationship furthermore remains valid when controlled against innovation-characteristics, socio-economic-, and geographical effects.

Lastly, the fact that both degree centrality (β = -,102, *p* = ,004) and eigenvector centrality (β = -,115, *p* = ,001) were negatively related to PM2.5 air emission uncovers two important findings. Firstly, it indicates that actual positioning in a multi-scalar knowledge network is of importance when sustainability performance for a given year is concerned. Secondly, the results tell us that when pollution for individual years is concerned, core regions are likely to be less pollutant, and that peripheral regions are likely to be more pollutant. Combined with the results for the investigative analysis in the thesis, this implicates that regions in the network core are both less pollutant and more likely to be strong regions, while regions in the network periphery are both more pollutant and more likely to be modest regions.

5.3.2 Multiple regression analysis – dynamic effects

Multiple regression analysis was utilized to examine whether there were connections between regional centrality scores, and changes in regional sustainability performance over a three-year period (2018-2021). Individual analyses were carried out for each of the centrality measurements (degree centrality, eigenvector centrality and closeness centrality) to assess the individual effect of each independent variable, reported as model 1, 2 and 3 respectively. Dynamic scores (measured as differences between 2018 and 2021 scores) were used for each of the remaining control variables.

Table 5: Summary of multiple regression analyses for dynamic effects (N = 223)

	Model 1			Model 2			Model 3		
	B	*SE B*	β	*B*	*SE B*	β	*B*	*SE B*	β
Degree	-,064	,031	-,133*						
Eigenvector				-,204	,098	-,133*			
Closeness							-,156	,053	-,187**
Tertiary education	,164	,053	,201**	,164	,053	,201**	,180	,053	,220***
Lifelong learning	-,191	,104	-,125	-,190	,104	-,124	-,178	,103	-,116
Non-R&D innovation expenditure	-,064	,030	-,150*	-,063	,031	-,146*	-,067	,030	-,157*
Innovation expenditure per person	,390	,070	,424***	,387	,070	,420***	,394	,069	,427***
Business process innovations	-,059	,021	-,202**	-,060	,021	-,204**	-,056	,021	-,193**
Knowledge-intensive activities	,181	,085	,124*	,183	,085	,136*	,197	,085	,146*
Country fixed effects		NO			NO			NO	

Note *p<,05, **p<,01, ***P<,001

In the first place, the overall regression was statistically significant for Model 1 ($R^2 = 0.18$, $F(7, 215) = 6.66$, $p = <.001$), Model 2 ($R^2 = 0.18$, $F(7, 215) = 6.66$, $p = <.001$), and Model 3 ($R^2 = 0.19$, $F(7, 215) = 7.40$, $p = <.001$).

Similarly to the static effect results, dynamic centrality measures were negatively related to PM2.5 air emissions in each of the models. This indicates that a higher centrality score is related to a gradual increase in regional sustainability performance over time. The fact that both degree centrality (β = -,133, p = ,038) and eigenvector centrality (β = -,133, p = ,038) were significantly related to air emissions indicate that actual positioning in the network matters; core regions are likely to be less pollutant for any given year and to have a greater increase in regional sustainability performance over time. However, the fact that closeness centrality (β = -,187, p = ,004) was also related to gradual increases in sustainable performance is interesting. This indicates that when long term changes in sustainability performance are concerned, key positioning in a multi-scalar knowledge network might be particularly important, as this entails a potential alternative strategy for less connected regions (I.e., peripheral regions).

Among the remaining control variables, Non-R&D innovation expenditures and business process innovations were statistically significant and negatively related to PM2.5 air emissions (i.e., related to increases in sustainability performance). On the other hand, tertiary education, innovation expenditure per person (employed), and knowledge-intensive activities were positively related to PM2.5 air emissions (i.e., related to decreases in sustainability performance). It should be noted that the variable "Lifelong learning" was significant at p = 0.66 – 0.88 which, while not significant at the traditional alpha level (p = 0.05), indicates that higher levels of lifelong learning might be related to gradual increases in regional sustainability performance.

All in all, the dynamic results indicate that connections to a multi-scalar knowledge network are positively related to changes in regional sustainability performance through gradual decreases in PM2.5 air emissions. This relationship remains valid when controlled against socio-economic effects, innovations characteristics and technological differences (knowledge-intensive activities).

Overall, our results indicate that strong regions are more likely to be situated in the core network, and modest regions are more likely to be situated in the periphery of the network. Furthermore, when a static approach is utilized, peripheral regions tend to be more pollutant (i.e., lower sustainability performance) than core regions. However, if we observe changes over time through a dynamic approach, the perspective seems to change as well. The results indicate that participation in the network over time is related to a positive effect on regional emissions and on sustainability performance by proxy. Both actual positioning in the core network and key positioning are related to gradual decreases in emissions. This in turn indicates that modest regions might potentially benefit from participation in the network over time through key positioning, in their efforts to strengthen their sustainability performance. With this in mind, strengthening participation in the EU FPs should represent a priority for less advanced and peripheral regions.

6. Discussion

A particularly interesting find in our thesis is the interplay between the results from the static and dynamic approach, and their implications for sustainability performance.

Using a static approach, we uncovered interesting findings regarding the relationship between connections to a multi-scalar knowledge network and regional pollution. In the first instance, there is a statistically significant relationship between both degree- and eigenvector centrality and regional pollution in our sample. This entails that being part of the core network is associated with lower pollution levels, while peripheral regions are more pollutant. This holds true whether the region has numerous ties to other regions or has direct connections to more central stronger regions. The results also show that this relationship is unaffected by geographical positioning and how advanced a given region is.

Strong regions with thick and diversified RIS are most often found in large core regions such as metropolitan areas and advanced technology regions (Asheim et al., 2019, p. 44). One might intuitively assume that such regions pollute more than peripheral/rural areas, but our results indicate that these strong regions, which are typically closely situated to the core of the network, are benefiting from their network position.

Furthermore, according to Asheim et al. (2011, p. 1137; Asheim et al., 2019, p. 44-45), peripheral regions tend to be associated by weaker types of RIS. Our results support this claim since our investigative analysis shows a relationship between the level of network centrality and RISB performance groups, with lower centrality scores being associated with weaker performance groups (see figure 3). Our results show that weaker regions have far less ties to other regions compared to stronger regions on average (see table 2). In fact, the maximum number of ties for any weak region (32 ties) was less than the average for all strong regions (44,75 ties) in the sample.

The combination of higher pollution levels and modest RIS appears to be increasingly problematic for peripheral regions on account of the limited potential for regional transformation within modest regions (Asheim et al., 2019, p. 51). All in all, the static results show that the core regions are typically less pollutant and are characterized by stronger RIS, which equips them with the necessary tools for dealing with pollution issues. Conversely, peripheral regions in the network seem to be both more pollutant and less equipped to deal with these issues compared to core regions, essentially trapping these regions in a negative spiral.

Using a dynamic approach, we found a statistically significant relationship between degree-, eigenvector-, and closeness centrality and changes in regional pollution. This finding is especially interesting in the context of the challenges peripheral regions are faced with, identified by the static approach. While the static approach identified challenges for peripheral regions, the dynamic approach presents a potential solution. Holding an actual positioning (degree- and eigenvector centrality) in the core of the knowledge network is not only associated with lower pollution levels for a given year, but also with gradual decreases in pollution over time. This entails a possible solution for peripheral regions, as securing a core position in the network, either through numerous ties to other regions or coordinated connections to strong regions, might provide the tools needed to reduce pollution over time. However, moving from the periphery to the core is difficult. Considering the fact that the maximum number of ties for any modest region was far lower than for the moderate or strong regions, this might represent an unrealistic solution.

On the other hand, the results show that holding a key positioning in the network is not only associated with decreases in pollution but might also be particularly important in this regard. Holding a key positioning entails reducing the number of ties needed to be indirectly connected to other regions in the network. Thus, by establishing ties to a select few regions with relevant connections to the overall network, peripheral regions can establish a key positioning in the network.

Through this strategy, peripheral regions might be able to extract the knowledge they need from stronger regions to battle their aforementioned challenges and reduce their pollution over time, without holding an actual position within the core network. This notion is furthermore supported by previous literature which argues that modest regions are typically dependent on path importation in order to facilitate path development (Asheim et al., 2019, p. 50-51). This highlights the importance for these regions to establish connections to external stronger regions (Tödtling & Trippl, 2005, p. 1214).

All in all, our results provide a satisfactory answer to research question 1; *«How can connection to multi-scalar knowledge networks explain variations in regional sustainability performance?»*. Holding an actual position within the core network is related to gradual increases in regional sustainability performance. However, peripheral regions might be able to bypass the need for an actual positioning, depending on whether these regions successfully secure a key position within the network. Therefore, it is arguably particularly important for these regions to participate in the EU framework programmes.

While the effects of connections to a multi-scalar knowledge network on regional sustainability performance is of main interest in this thesis, we also wanted to explore the effect of socio-economic, geographical and innovation characteristics on this relationship. Interestingly, among the static variables, only SMEs collaborating, which is the only static economic variable that incorporates a relational approach, was significantly related to air emissions levels. Earlier studies have shown that enterprises in general can benefit from collaboration in their innovation efforts, but SMEs in particular can benefit from collaboration with other SMEs in the same network in their efforts to obtain resources for innovation (González-Benito et al., 2016, p. 658). For this reason, our assumption is that SMEs that obtain resources through collaboration are better equipped to develop solutions for mitigating and reducing pollution. This assumption is further strengthened by the network centrality – air pollution relationship shown in our main results. It is furthermore worth noting that a study by Man & Duysters (2005, p. 23) found that firms which collaborate or enter alliances with others, perform better in innovation than firms that acquire external knowledge through mergers or acquisitions of other firms. This underlines the importance of growth through engaging in multi-scalar knowledge networks.

For the remaining static variables, neither GDP, public R&D expenditure nor business R&D expenditure were significantly related to emission levels. This indicates that the effect of connections to a multi-scalar knowledge network on regional emissions is independent of how advanced a given region in the network is. Furthermore, the static models were not invalidated by country fixed effects, indicating that the network centrality – air pollution relationship exists independently of the geographical positioning of regions.

Among the dynamic variables, Non-R&D innovation expenditure (per person employed) and business process innovations were statistically significantly related to gradual decreases in regional emissions. Non-R&D innovation in this context relates to investments into new technology through equipment, machinery, patents, etc. (European Commission, 2021, p. 55). Considering new advances in sustainable technologies through smart energy systems, low carbon technologies and novel energy materials, especially in the post COVID-19 era (Chong et al., 2022), it is possible that an adequate portion of Non-R&D expenditure is related to such technologies. Acquisition of such technologies could perhaps contribute to gradual reductions in air emissions. Concerning business process innovations, our results might be explained by recent trends in industrial sectors such as tourism and hospitality. These trends show that companies are increasingly introducing sustainability through green innovations into their business model for the purpose of innovating and creating competitive advantages (Presenza, 2019). While lifelong learning was not significantly related to changes in regional emissions in our sample (p = 0.66 – 0.88 across dynamic effect models), it is worth noting that previous studies have linked knowledge of climate change causes to increased public climate concern (Shi et al., 2016, p. 759) and environmentally responsible behavior (Fransson & Garling, 1999, p. 373). If one assumes that higher levels of learning activities in general also leads to increases in climate change knowledge, then one could perhaps also assume that this leads to increases in environmentally friendly behavior, which in turn leads to reduced air emissions. However, this requires a number of interlinked assumptions and likely ignores other important factors, which might explain why this relationship was ultimately non-significant.

Furthermore, knowledge intensive activities, tertiary education and innovation expenditure per person were statistically significantly related to gradual increases in regional emissions. Knowledge intensive activities in this context includes industries such as aerial transport, computer manufacturing and production of petroleum products (Eurostat, n.d.). As such, it is not surprising that increases in knowledge intensive activities are related to increases in pollution over time. Concerning tertiary education, one could at first glance perhaps expect this variable to be associated with decreased emissions over time, especially considering the non-significant results for lifelong learning previously mentioned. However, we suspect that this result might be more related to geographical effects, as tertiary education levels in EU are higher in urban areas than rural areas (Popescu et al., 2022). As such we suspect that this effect might in reality relate to pollution levels in urban and rural areas in the EU. The association between innovation expenditure per person (in SMEs) and increases in regional pollution was unexpected, especially considering that both Non-R&D innovation (expenditures) and business process innovations (SMEs) were related to gradual decreases in pollution. It should be noted that the variable specifically measures monetary input into innovation activities (European Commission, 2021, p. 57), and the distribution of input into attempted innovations and successful innovations is unclear. We hypothesize that these results might be credited to resource usage for innovation attempts which ultimately fail, but more research is needed on this relationship.

All in all, these results provide a satisfactory answer to research question 1.1; *«How does regional socio-economic, geographical and innovation characteristics contribute to this? (I.e., the relationship between connections to multi-scalar knowledge networks and regional sustainability performance)».* While regional socio-economic-, geographical- and innovation characteristics varies in their contribution to the relationship between multi-scalar knowledge networks and regional sustainability performance, the overall relationship remains valid in the face of these effects.

The results indicate important implications for both local and global policies for network collaboration and innovation. While our results show that peripheral regions might potentially strengthen their sustainability potential through reduced pollution by participating in the knowledge network, facilitating the opportunity for participation comes with its own set of challenges. Our investigative analysis shows tendencies of an oligarchic core which means that strong regions tend to communicate more with each other in a tight knit group of highly diversified and well-developed regions. We found, like previous studies on participation in EU FPs (Calignano & Trippl, 2020), that participation is skewed, and most peripheral regions do not participate as often or with as many regions, as core regions.

Previous studies by Calignano & Trippl (2020, p. 14-15) have suggested that such issues could be tackled through challenge-driven participation. As suggested by this study, this could in our case be interpreted as allocating funding to each peripheral region in order to involve at least one organization from these regions to stimulate inter-regional collaboration and knowledge circulation.

The fact that key positioning can provide a potential solution for peripheral regions could imply that regional, national, and global policymakers should support weaker regions in attaining a key position by situating them in the network in such a way that they can extract important knowledge. However, not all governments are equal in their ability to foster regional innovation. A study by Rodríguez-Pose & Di Cataldo (2015, p. 693) identified lack of policy-making capacity and corruption as the main threat to knowledge generation.

Even in scenarios where governmental efforts to foster knowledge generation are satisfactory, it is likely crucial that these regions are able to utilize the affordances of a key network position in an advantageous manner for this to be effective. Wang et al. (2018) found that the effect of knowledge network participation is mediated by participants ability to integrate new knowledge and apply it in combination with existing knowledge. Wang et al. (2018) findings could imply that just attaining a favorable position in a knowledge network, and thus having access to new knowledge resources, does not solve the problem by itself. New-to-region knowledge must likely be understood and integrated in the regions’ existing knowledge base for it to have any effect on regional sustainability performance.

6.1 Limitations:

Due to how we chose to study knowledge networks, we had to adapt a very overarching view of knowledge transfer. Firstly, we only examine knowledge which is (relatively) easily transferred across geographical distances. This rendered us less able to consider the effects of local knowledge spillover effects on neighboring regions, as well as how regional sustainability performance is affected by synthetic and symbolic knowledge. It is worth noting however that previous studies have indicated that knowledge spillover effects are somewhat rare in peripheral regions (Rodríguez-Pose & Di Cataldo, 2015, p. 687-688).

Secondly, the perspective of our thesis made us more able to discuss general tendencies in the network as a whole, but simultaneously less able to study participation effects for a specific region. We also chose to use normalized scores for our analyses. We were most interested in the overall relationships between connections to a multi-scalar knowledge network and sustainability performance. We wanted to know whether different types of participation and different modes of centrality/positioning in a knowledge network was related to increases or decreases in regional pollution and whether participation in such a network could be used as a tool for strengthening sustainability performance in different types of regions.

Furthermore, we limited us to PM2.5 emissions. There are different climate-related emissions, but we chose PM2.5 due to it being the most harmful to the human population, and also directly related to fossil fuel consumption.

7. Conclusion

The findings in our thesis show that connections to a multi-scalar knowledge network have an effect on regional sustainability performance. Actual positioning within the core network was related to gradual increases in sustainability performance through reductions in air emissions. However, by switching from a static approach to the dynamic approach, the perspective changed too. This perspective indicates that peripheral regions which are not performing well can use the same network to combat their issues with pollution through key positioning, and thus strengthen their sustainability performance. Based on this, local and global policymakers should make increasing efforts to include peripheral and struggling regions in the EU framework programmes.

Future recommendations

While our thesis gives an account of the relationship between connections to a multi-scalar knowledge network and regional sustainability performance at the EU level, we believe it would be interesting to apply the findings from our thesis to specific regions, countries or groups of regions such as the EU13 and EU15. One of the original aims of our thesis, was to apply our findings to the context of Norway. We wanted to examine which of these regions, if any, functioned as gatekeepers, brokers, etc., of knowledge and how different Norwegian regions could adapt to the Norwegian part of our knowledge network to strengthen their sustainability performance. Due to time constraints however, we chose to omit this in our thesis. We, or others will hopefully study this in a Norwegian context in the near future.

It would also be interesting to study similar knowledge-networks and their effects in other parts of the world outside the EU. For instance, Central-Asia, and specifically China have recently become a focus point for literature on the relationship between knowledge networks and sustainability (Pu et al., 2022; Losacker, 2022), as well as on the relationship between innovation and sustainability (Wang et al., 2022). Studies of similar pan-continental knowledge networks could provide valuable information about how different cultures affect innovation capabilities and collaboration in knowledge networks.

Alternatively, we suggest that our findings can serve as a framework for similar studies of knowledge networks on a smaller scale, for example limited to a country, region or regional innovation system. Further additions to the literature could also examine if the tendencies between regions in Europa also can be found between smaller clusters of firms and organizations.

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Appendices

Appendix A: Terminology

Sustainable Innovation	"Innovation in which the renewal or improvement of products, services etc. [..] not only delivers an improved economic performance, but also an enhanced environmental and social performance, both in the short and long term have the capacity to generate positive social and environmental impacts" (Bos-Brouwers, 2010, p. 422).
Green Innovations	*"The development of new knowledge which is implemented into a new product, process or service which generates profit while simultaneously reducing the total environmental impact in one or more phases of the product, process or services life course"* (Arnekleiv & Larssæther, 2004; Aasen & Amundsen, 2015, p. 43: Our translation).
Differentiated knowledge bases	A theoretical concept for analyzing different kinds of knowledge. Knowledge types are categorized as: Analytical (codified) knowledge, Symbolic (tacit) knowledge and Synthetic (a combination of both tacit and codified) knowledge (Asheim et al. 2019, p. 38-39, Chen & Hassink, 2020, p. 2491).
Regional innovation systems	Innovation systems are generally made up of linkages between different actors, agencies and organizations that contribute to promoting innovation in their society/region societies (Asheim et al. 2019, p. 8). One typically differentiates between three main types of RIS, based on their potential for innovation, interactive learning, and entrepreneurship. The three main types of RIS are; thick and diversified RIS, thick and specialized RIS, and thin RIS (Asheim et al, 2019, p. 44-45).
Knowledge networks	A knowledge Network involves a given number of resources and actors who are able to obtain, share and create new knowledge through cooperation, with the goal of value creation (Du Preez et al, 2008, p. 159).

Appendix B

In depth information about dependent, independent and control variables

Dependent variable				
Category	Name	Indicator	Variable type	Description
Sustainability	Air emissions (PM2.5)	Exposure to fine particulates (PM2.5)	Static (2018 scores) & Dynamic (changes in 2018 - 2021 scores)	This indicator captures exposure to PM2.5 air emissions in regional populations. Changes in exposure values provide a key proxy measure for regional sustainability performance. Dynamic variable (2018-2021) on continuous scale. Normalized on a -1 to 1 scale. Source: European Commission
Independent variables				
Category	Name	Indicator	Variable type	Description
Centrality measure	Degree	Degree centrality H2020-Energy	Semi-dynamic (based on total number of collaborations from 2014 – 2020 period)	Degree centrality; number of ties a node has to other nodes in the H2020-Energy network. Continuous variable. Normalized on a 0-1 scale. Source: CORDIS
Centrality measure	Closeness	Closeness H2020-Energy	Semi-dynamic (based on total number of collaborations from 2014 – 2020 period)	Closeness centrality: Mean score of the shortest paths between a given node and every other node in the network. Continuous variable. Normalized on a 0-1 scale. Source: CORDIS
Centrality measure	Eigenvector	Eigenvector H2020-Energy	Semi-dynamic (based on total number of collaborations from 2014 – 2020 period)	Eigenvector centrality: Measurement of a node's connection to the most influential nodes in the H2020-Energy network. Continuous variable. Normalized on a 0-1 scale. Source: CORDIS

Control variables				
Category	Name	Indicator	Variable type	Description
Socio-economic	Tertiary education	Percentage of population aged 25-34 having completed tertiary education	Dynamic (changes in 2018 - 2021 scores)	A general indicator of advanced skills. The variable has a narrow focus on population (age 25-34) to quickly reflect changes in educational policy. Number of individuals aged 25-34 with some form of post-secondary education divided by total population age 25-34 Dynamic variable (2018-2021) on continuous scale. Normalized on a -1 to 1 scale. Source: European Commission
Socio-economic	Lifelong learning	Percentage population aged 25-64 participating in lifelong learning	Dynamic (changes in 2018 - 2021 scores)	Encompasses all purposeful learning activity (both formal and informal) undertaken with the aim of improving knowledge, skills and competences. Persons (private household) between 25-64 who have participated in any education or training (regardless of relevance) in the last 4 weeks prior to interview divided by total population between 25-64 (European Commission, 2021). Dynamic variable (2018-2021) on continuous scale. Normalized on a -1 to 1 scale. Source: European Commission
Regional innovation characteristics	Non-R&D innovation expenditure	Non-R&D innovation expenditures in SMEs as percentage	Dynamic (changes in 2018 - 2021 scores)	Measures non-R&D innovation expenditure (e.g investment in equipment, machinery, acquisition of patents and

		of turnover		licenses). A measure for the diffusion of new production tech and ideas. Sum of total innovation expenditure excluding intramural and extramural R&D expenditures divided by total turnover for SMEs Dynamic variable (2018-2021) on continuous scale. Normalized on a -1 to 1 scale. Source: European Commission
Regional innovation characteristics	Innovation expenditure per person	Innovation expenditures per person employed (SMEs)	Dynamic (changes in 2018 - 2021 scores)	This indicator measures the monetary input directly related to innovation activities Sum of total expenditure by enterprises (all sizes) in PPS (purchasing power standard) divided by total employment in innovative enterprises SMEs. Dynamic variable (2018-2021) on continuous scale. Normalized on a -1 to 1 scale. Source: European Commission
Regional innovation characteristics	Business process Innovations	SMEs introducing business process innovations as percentage of SMEs	Dynamic (changes in 2018 - 2021 scores)	Product innovation is a key ingredient to innovation as they can produce new markets and improve competitiveness. A higher share of product innovators reflects a higher level of innovation activities. The number of SMEs who introduced at least one product innovation divided by total number of SMEs. Dynamic variable (2018-2021) on continuous scale. Normalized on a -1 to 1

				scale. Source: European Commission
Regional innovation characteristics	Knowledge-intensive activities	Employment in knowledge-intensive activities as percentage of total employment	Dynamic (changes in 2018 - 2021 scores)	Knowledge-intensive activities provide services directly to consumers and provide input to the innovative activities of other firms in all sectors of the economy. The number of people employed in knowledge-intensive activities in business industries divided by total employment Dynamic variable (2018-2021) on continuous scale. Normalized on a -1 to 1 scale. Source: European Commission
Regional innovation characteristics	SMEs Collaborating	Innovative SMEs collaborating with others as percentage of SMEs	Static (2019 scores)	The indicator measures the degree to which SMEs are involved in innovation cooperation. Complex innovations often depend on companies' ability to draw on diverse sources of information and knowledge, or to collaborate on the development of an innovation. The indicator measures the flow of knowledge between public research institutions and firms, and between firms and other firms. Number of SMEs with innovation co-operation activities divided by total number of SMEs
Regional innovation characteristics	Public R&D exp	R&D expenditure in the public sector as percentage of GDP	Static (2019 scores)	R&D expenditure represent one of the major drivers of economic growth in a knowledge-based economy. Trends in R&D expenditure indicator provide

				indications of the future competitiveness and wealth of a region. R&D spending is essential for making the transition to a knowledge-based economy as well as for improving production technologies and stimulating growth. All R&D expenditure in the government- and higher education sectors divided by Regional GDP.
Regional innovation characteristics	Business R&D exp	R&D expenditure in the business sector as percentage of GDP	Static (2019 scores)	This indicator captures the formal creation of new knowledge within firms. Particularly important for the science-based sector where most new knowledge is created in or near R&D laboratories. All R&D expenditures in the business sector divided by Regional GDP
Economic	GDP	Gross domestic product	Static (2018 scores)	The total value of goods and services produced by a country in a year. Source: Cambridge Dictionary
Geographical	Country fixed effects	Country fixed effects	Static (constant)	Binary variable. Signifies whether a given region belongs to a given country or not.

Appendix C: SNA figures

Full size versions of SNA figures (figure 3 – 3g) (see figure 3 for legend).

Figure 3

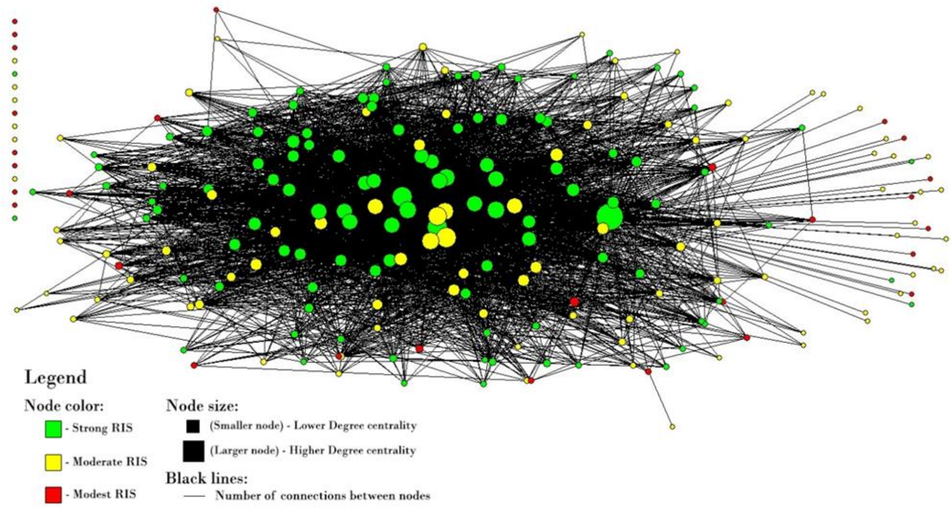

Figure 3b: Strong and moderate RIS regions (Modest regions excluded)

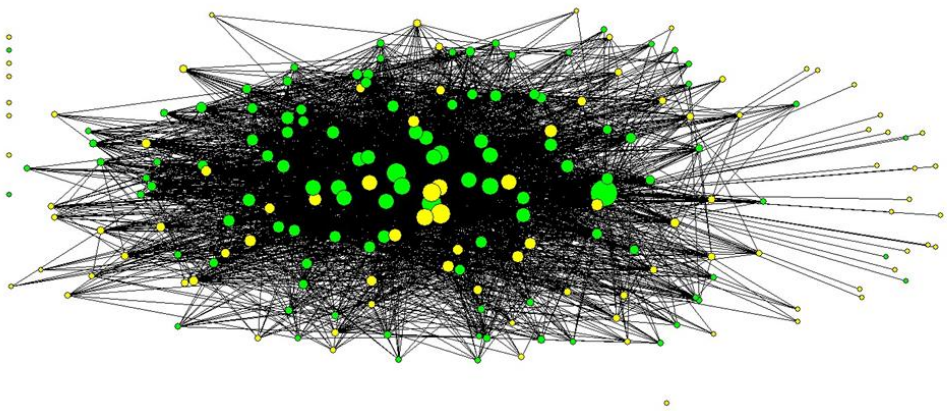

Figure 3c: Moderate and modest RIS regions (Strong RIS regions excluded)

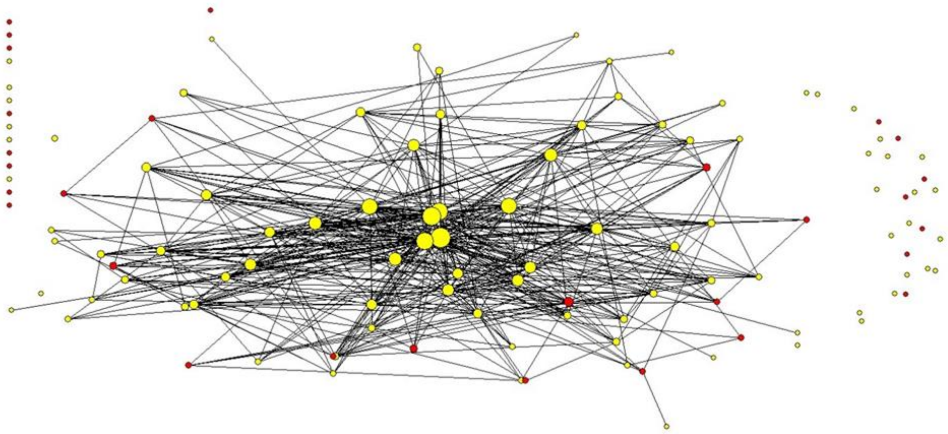

Figure 3d: Strong and modest RIS regions (moderate regions excluded)

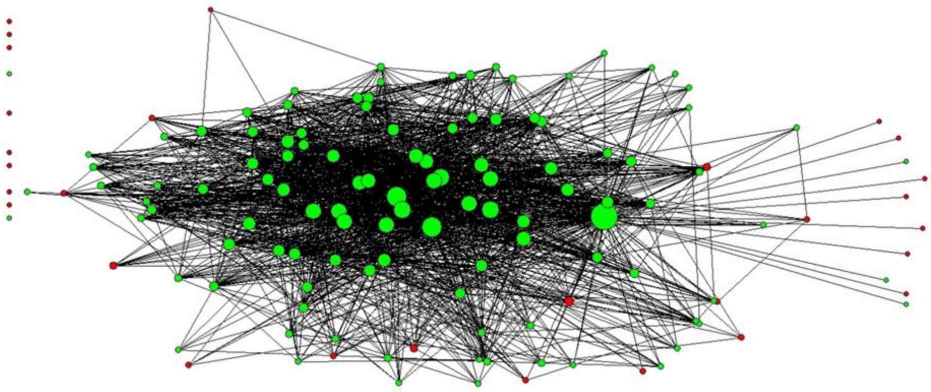

Figure 3e: Modest RIS regions (strong and moderate regions excluded)

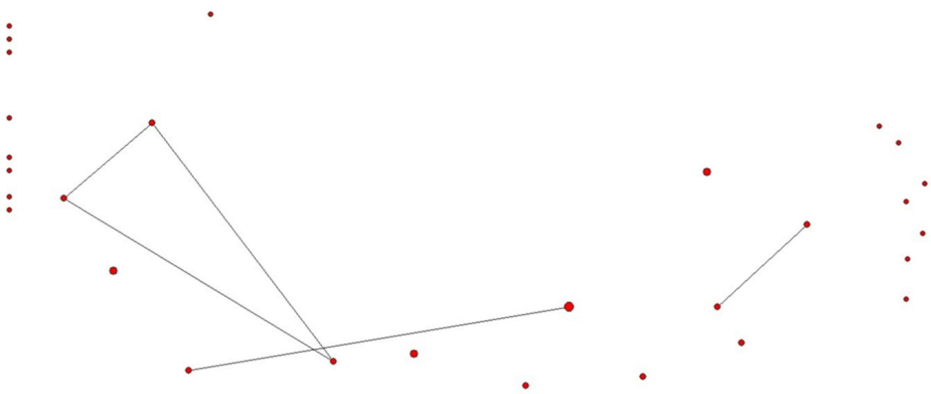

Figure 3f: Moderate RIS regions (Strong and moderate regions excluded)

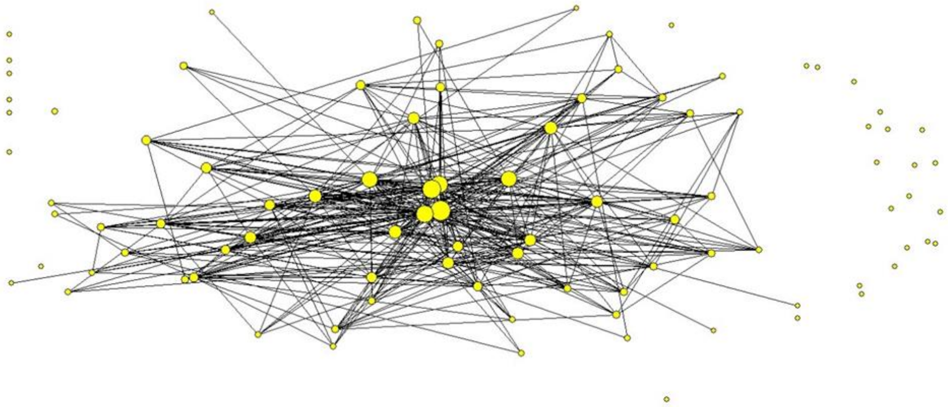

Figure 3g: Strong RIS regions (Moderate and modest regions excluded)