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Exploring the regional patterns of complex knowledge production: the case of renewable energy technologies in the European Union

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CWTS
Meaningful metrics

Abstract

European regions are currently implementing smart specialisation strategies trough the capitalisation of their knowledge assets to drive innovation in promising sectors, fields or technologies . However, there is a lack of understanding behind the knowledge development process of smart specialisation strategies targeting renewable energy technologies. Especially so in the creation of complex knowledge, which is more difficult to replicate and it therefore provides a greater competitive advantage. This research aims to fill that gap by exploring the patterns of complex knowledge production in six renewable energy technologies. By making use of quantitative methods and building upon the theoretical foundations of Evolutionary Economic Geography and the Smart Specialisation literature, this research attempts to test the relationship between the ability of a region to create complex knowledge and four mechanisms of path and place dependency linked to the knowledge creation process. Scientific publications cited in patents are used as an indicator for regional knowledge production to capture the role that scientific knowledge plays in technological development. A set of quantitative analysis revealed that scientific relatedness is the most important driver for the creation of complex knowledge. That is the extent to which a region's scientific profile is related to the knowledge base of a given technology. Contrary to what was expected, the results showed that the infrastructural and technological carbon lock-in of fossil fuel technologies either constraint or encourage the creation of complex knowledge. Moreover, it was found that the ability of a region to create complex knowledge does not depend on its ability to accumulate scientific knowledge, being solar PV technology the exception, possibly due to the high level of analyticity of its knowledge base. Unexpectedly, the access to complementary knowledge trough interregional linkages does not have a strong impact in the creation of complex knowledge. Instead, it is possible that complex knowledge is more likely to be geographically bounded. This is supported by the spatial distribution of complexity scores, in which high-score regions tend to cluster next to each other. To conclude, the findings of this research suggest that European regions implementing smart specialisation strategies targeting renewable energy technologies are more likely to be successful when they diversify into scientific or technological fields that are related to their scientific profile, regardless of their capacity to contribute to the knowledge stock or the knowledge and specialised skills accumulated in fossil fuel technologies.

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1. Introduction

Climate change is among the main drivers of the European energy transition (Gielen et al., 2019) and the European Commission has established an ambitious target to reduce greenhouse gas emissions by 40% and increase the share of renewable energy by 32% by 2030. (European Commission, 2017). Within this context, the European Union introduced the smart specialisation policy framework to support sustainable transitions (S4+) by prioritising promising sectors, fields or technologies. Currently, renewable energy is one of the main priorities for many regions and two-thirds already have a clean energy-related priority (European Commission, 2018; Steen et al., 2018). Regions are therefore playing a more important role in fostering renewable energy, translating into a direct contribution towards the climate and energy European targets (European Commission, 2018). Within the smart specialisation policy framework both a region's knowledge assets and its local capabilities are considered to be the building blocks to drive innovation (Foray et al., 2011). Consequently, there is an important societal need to understand the dynamics behind the knowledge development process that supports sustainable energy innovations (Steen et al., 2018), and more specifically for the creation of complex knowledge, as it is more difficult to replicate and, therefore, provides a greater competitive advantage (Pintar & Scherngell, 2018). Even tough numerous studies have explored the regional knowledge creation process, it is not clear whether their findings can be extended to specific sectors or to technological fields. Therefore, further research is needed to explore the patterns of knowledge production of renewable energy technologies (Steen et al., 2018).

Previous research has demonstrated that knowledge production has different patterns in the geographical space; and it depends to a greater extent in the scientific and technological capabilities available. Since the knowledge development process is differentiated across locations, knowledge tends to remain unevenly distributed in space (Balland & Rigby, 2016; Heimeriks et al.,2019; Pintar & Scherngell, 2018); and some regions struggle to replicate the levels of productivity and innovativeness achieved in leading regions (Heimeriks & Balland, 2016). In terms of diversification opportunities, previous research suggests that regions are more likely to diversify into activities related to their existing scientific profile, discouraging efforts on activities unrelated to their knowledge assets (Boschma et al., 2014a; Heimeriks et al., 2019). From the perspective of knowledge complexity, Balland et al. (2018) found that regions are more likely to diversify into new complex technologies when they tend to build upon their local capabilities. For the case of renewable energy technologies, Li (2020) also found that the scientific profile of countries facilitates the early adoption of breakthrough innovations in solar photolytic and wind power technologies. At the same time, the ability of a region or country to participate in the development on a renewable energy technology, depends not only on the locally available knowledge and capabilities, but also on the characteristics of a given technology's knowledge base (Li, 2020; Persoon et al., 2021). Lastly, different types of carbon lock-ins are likely to limit the knowledge development in renewable energy technologies (Seto et al, 2016.)

Overall, scholars have demonstrated that complex knowledge creation is a geographically differentiated phenomenon, partially constrained by regional capabilities. Their contributions are important steppingstones towards understanding the implications of the knowledge creation process for place-based innovation policies. However, no studies as to date have explored the regional patterns of complex knowledge production in renewable energy technologies. Moreover, it is not clear the extent that the infrastructural and technological carbon lock-in hamper the knowledge creation process around sustainable energy technologies. Therefore, it remains unclear whether the findings of previous research can be generalised in the field of renewable energy. Especially, empirical evidence is required to determine whether the diversity and uniqueness of a region's scientific portfolio influences its capacity to develop complex knowledge in renewables energy technologies. This is highly relevant for the smart specialisation policy framework, whose rationale lies on the assumption that regions need to focus on their local capabilities to realise the scaling potential of new domains (Foray et al., 2011). In addressing the previous research gaps, the core question that motivates this research is the following:

- What are the regional patterns of complex knowledge production in renewable energy technologies?

From a spatial and evolutionary perspective, this question aims to find specific trends as European regions engage in the knowledge development process within the renewable energy field. More particularly, this research attempts to answer the following sub questions:

- To what extent does the scientific portfolio of a region influence its further capacity to produce unique and diversified knowledge in renewable energy technologies?

This question aims to prove whether local capabilities depicted by the scientific specialisation of a region determine its capacity to produce more unique and diversified knowledge.

- To what extent does the capacity of a region to contribute to the knowledge stock facilitate the further development of complex knowledge?

This question aims to find whether the knowledge accumulated in a region influences its capabilities to produce unique and diversified knowledge.

- To what extent does the carbon-emitting energy infrastructure constrain the production of complex knowledge in renewable energy technologies?

The aim of this question is to resolve whether the specialised skills and knowledge accumulated within carbon-emitting energy infrastructure in a region somehow affects its capacity to produce unique and diversified knowledge in renewable energy technologies.

- To what extent are regions with access to complementary knowledge trough interregional networks more likely to develop complex knowledge in renewable energy technologies?

This question intends to evaluate whether access to complementary knowledge available in other locations influences the capacity of a given region to develop unique and diversified knowledge.

In answering those questions, this research makes use of quantitative methods and bridges theoretical concepts from the Evolutionary economic geography and smart specialisation literature. Scientific publications cited in patents are used as an indicator for regional knowledge production to capture the role that scientific knowledge plays in technological development. By gathering scientific publications cited on patents, an original methodological approach is introduced to calculate a knowledge complexity index for European regions within the cognitive limits of renewable energy technologies. Other energy indicators are collected from the Eurostat database to test the relationship of knowledge complexity with mechanisms of path and place dependency within the knowledge production process. Overall, this study, offers an innovative analytical and methodological approach to study the regional patterns of knowledge production in renewable energy technologies.

This study follows a recent research stream measuring knowledge complexity from an evolutionary perspective, focusing on the regional level of analysis and taking the case of renewable energy technologies. By exploring the determinants of knowledge complexity from an evolutionary perspective, this research attempts to contribute to the body of knowledge of Evolutionary economic geography. In doing so, this research aims to bring new insights regarding the constraints and opportunities imposed by the current scientific and technological trajectories in the field of renewable energy. Moreover, new insights into the potential constraints of the technological and infrastructural carbon lock-in of established fossil-fuel technologies in the knowledge production process are expected to emerge. This research also aims to bring new evidence between the relationship of knowledge accumulation in certain locations and their factual capacity to develop complex knowledge. Furthermore, an attempt is made to bridge the gap regarding the potential and positive externalities that the access to complementary and external knowledge might have over the production of complex knowledge. Ultimately, this research attempts to bring new insights into the implications of smart specialisation strategies for decarbonising the energy systems while creating competitive advantages for European regions.

A better understanding of the regional patterns of knowledge production in renewable energy technologies has important implications for the design and implementation of smart specialisation policies in Europe targeting clean energy-related priorities. As an ex-ante condition for receiving European Structural and Investment Funds the European Commission has encouraged regions to implement smart specialisation strategies (Steen et al., 2019). To unfold those strategies, smart specialisation policies have been deployed so as to support the energy system transformation (Steen et al., 2019). This transformation requires the creation and diffusion of scientific and technical knowledge to drive innovation (Gallagher et al., 2012). Thus, it is necessary to acknowledge the process behind 'what a region does best in terms of its scientific and technological endowments' (Morisson & Pattison, 2020). Because smart specialisation is fundamentally a place-based innovation policy concept, a better understanding of the territorial diversity and the best opportunities for further knowledge development at different locations is required (Heimeriks et al., 2019). Furthermore, recognising the place-specificity in developing clean technologies is crucial for formulating better energy transition pathways for individual locations (Li, 2020). Overall, a better understanding of the knowledge creation process may allow policy makers to make better choices when it comes to the design and implementation of smart specialisation strategies targeting renewable energy technologies.

2. Theoretical framework

The basic concern from Evolutionary economic geography lies within the mechanisms by which the economic landscape is transformed over time; being the development of knowledge the underlying driver of economic evolution (Boschma & Martin, 2010). The importance of knowledge in the economic transformation is recognised by the smart specialisation strategy policy concept, which aims to generate knowledge around a region's new domain of potential diversification with growth potential (Foray et al., 2011). In the following sections, a further elaboration of theoretical framework is provided. To begin with, a conceptualisation and a typology of the different types of knowledge base is presented. Afterwards, an interplay between smart specialisation and knowledge complexity is introduced. Lastly, four mechanisms of path and place dependency in the process of regional knowledge production with a focus on the energy field are described.

2.1 The knowledge base

The knowledge base concept has been mainly used to classify industries in terms of the ideal prototype of knowledge underlying the innovation process (Davids & Frenken, 2017). However, it has also been applied to regions (Asheim & Coenen, 2005), organizations (Davids & Frenken, 2017) and technologies (Persoon et al., 2021). In this research, this concept is used to describe the collection of scientific publications attributed to a given technology, while the term of 'scientific portfolio' is used to describe the share of a region's scientific publications within the knowledge base of a given technology. Additionally, the classification of Persoon et al. (2021) is used to describe the type of knowledge base of renewable energy technologies. Thus, it is possible to distinguish between two types of knowledge base: an analytical one and a synthetic one. In an analytical knowledge base, scientific knowledge is highly important, and knowledge creation is often based on cognitive and rational processes. This type of knowledge base is often associated with basic research and codified knowledge (Persoon et al., 2021), which is usually documented in reports, electronic files or patent descriptions (Asheim & Cohen, 2005). A typical example of a technology that relies on an analytical knowledge base is solar photovoltaics (Persoon et al., 2021). On the other hand, in a synthetic knowledge base, innovation takes place mainly through the application of existing knowledge or trough new combinations of existing knowledge. This type of knowledge base is usually associated with applied research and tacit knowledge (Persoon et al., 2021). Wind power, solar thermal, geothermal and hydropower represent examples of technologies that rely on a synthetic knowledge base (Persoon et al., 2021). This classification is useful to differentiate the type of knowledge that can be used in smart specialisation strategies. The body of scientific and codified knowledge of scientific publications cited in patents is used to construct the knowledge base of the technologies analysed.

2.2 Smart specialisation and knowledge complexity

Smart specialisation strategy is a place-based innovation policy concept to support regional prioritisation in innovative sectors, fields or technologies (Foray et al., 2011). This policy concept highlights the role of the entrepreneurial knowledge, which is a combination of knowledge about science, technology an engineering with knowledge of market potential, customers, and the whole set of inputs and services for launching a new activity. The entrepreneurial knowledge is used in the entrepreneurial discovery process to reveal what a region does best in terms of its scientific and technological endowments (Morrison & Pattison, 2020). In this research, the interest lies in the knowledge about science, technology and innovation, which is linked to the transformation of the economic structure toward a desirable trajectory of regional growth (Pinto et al., 2019). For this policy concept, promoting knowledge production in certain domains of future specialisation is considered a key driver for diversification (Foray et al., 2011). Every region has its own unique, scientific profile (Heimeriks et al., 2019), which determines their ability to develop new sectors or new market niches (Boschma & Martin, 2010). Therefore, the regions' scientific existing portfolios offer opportunities for related diversification and discourage the creation of knowledge in scientific fields unrelated to the local knowledge base (Heimeriks et al., 2019). In principle, the more complex the knowledge is produced, the more capabilities regions possess to easily diversify into new topics and fields (Heimeriks et al., 2019).

The notion of knowledge complexity has come into use as an attempt to measure quality of knowledge in terms of its uniqueness and its replicability. The central assumption is that more complex knowledge is more difficult to replicate, and therefore, provides a higher competitive advantage (Pintar & Scherngell, 2018). The variety of knowledge that a region possesses, but also the extent to which it is able to combine this knowledge, strongly determines the number of capabilities within that region (Hausmann et al., 2013). Regions that combine their capabilities in an efficient and unique way are able to develop new knowledge with greater complexity than that of other regions which are not capable to do so (Hidalgo & Hausmann, 2009). In other words, knowledge complexity can be explained by two dimensions - diversity and ubiquity - where diversity refers to the capabilities of regions with a diverse range of technologies; and ubiquity suggests whether the regions are capable to develop unique technologies. High diversity and low ubiquity contribute to a more complex knowledge structure of the region (Balland et al., 2018). Knowledge complexity provides a qualitative measure to inform smart specialisation strategies about which scientific areas or technologies are more worthy of prioritisation. More particularly, this qualitative measure is especially relevant for renewable energy technologies, which are considered complex technologies which require a greater variety of knowledge inputs and unique combinations of knowledge, in comparison to other technologies (Barbieri et al., 2020).

2.3 Regional knowledge production

From an evolutionary perspective, the knowledge production process can be fundamentally characterised as a path and place-dependent phenomena. Although path-dependency and place-dependency refer to two distinct mechanisms, they interact with each other in the knowledge production process (Li, 2020). Regions differ markedly in economic structure, institutions and connections to other regions; so the nature and degree of path dependency in the knowledge production vary from region to region, which makes path dependency a place-dependent process. (Martin & Sunley, 2006). In the following sections, a conceptual definition and some specific mechanisms of path and place dependency are introduced in more detail.

2.3.1 Path dependency

The core assumption of path dependency is that the continuous accumulation of knowledge leads to the formation of a technological trajectory, which defines the technological opportunities for further development (Dosi, 1982; Nelson & Winter, 1982). Innovative activities are strongly selective and actors that innovate will seek to improve and to diversify their technology by searching in zones that enable them to use and build upon the existing technological knowledge base (Dosi, 1988). From a smart specialisation perspective, it means that regions tend to diversify into new related activities based on the characteristics of their scientific profile (Boschma et al., 2014a). Given the high barriers of radical innovations of energy systems (Simmi et al.,2014), both the scientific profile of a region and the knowledge and skills accumulated with established fossil fuel technologies (Foxon, 2002; Seto et al., 2016; Unruh, 2000), represent important mechanisms of path-dependency while diversifying into new renewable energy technologies. Those two mechanisms of path dependency are explained in more detail below.

2.3.1.1 Scientific relatedness

Scientific relatedness can be conceptualised as a special case of path-dependence measured from a scientific knowledge production perspective. The relatedness concepts rests on the idea that the knowledge accumulated has an architecture that is based upon similarities and differences in a way that various types of knowledge can be used; when knowledge subsets are close to each other or demand similar sets of cognitive capabilities and skills for their use, they are related or proximate to each other in some form of knowledge "space" (Balland et al., 2018). Thus, the development of new scientific knowledge within a region reflects the existing collective capacity of the scientific community to build upon the accumulated knowledge, which in turn, is delimited by specific technological trajectories. In that sense, scientific relatedness is driven by the scientific specialisation of regions in specific technological trajectories. Since the scientific profile of a region determines their capacity to develop new knowledge in a specific scientific subfield (Heimeriks & Balland, 2016) and countries diversify toward green technologies that are related to their existing competences (Perruchas et al., 2020); it is therefore expected that the production of knowledge is driven by the scientific specializations of regions among specific technological trajectories. In particular, it is easier for regions to diversify into new complex technologies when they build on their local capabilities and the knowledge accumulated within their own scientific profile. This reasoning leads to the following hypothesis:

H1. Regions are more likely to produce complex knowledge in renewable energy technologies that are related to their scientific profiles.

2.3.1.2 Technological and infrastructural carbon lock-in

Carbon lock-in is a special case of path-dependency driven by the inertia of mutually reinforcing technologies, institutions and behavioural norms that limit the transformation rate of the global energy system due to increasing returns of scale (Seto et al., 2016). Without neglecting the importance of institutions and behavioural norms, this research focuses on a type of carbon lock-in associated with the technologies and infrastructure that shape energy supply and indirectly or directly emit CO_2 (Seto et al., 2016). The infrastructural and technological carbon lock-in concept derives from the assumption that the long life of physical infrastructure may lock societies into carbon-intensive emission pathways that are difficult to change due to differences in capital and operating costs, in comparison to low-carbon energy technologies (Klitkou et al., 2015; Seto et al., 2016). Thus, the adoption of low-carbon technologies is not economically favourable until capital and operating costs are less than those of incumbent fossil fuel–burning technology; which is unlikely to happen during their normal lifetime (Seto et al., 2016). Moreover, increasing returns of learning effects reduce the cost of research activities because of the specialised skills and knowledge accumulated trough production and market experience; which in turn, facilitate the development of higher quality products and the improvement of processes by incremental innovation (Antonelli, 2010; Klitkou et al., 2015). Therefore, it is expected that specialised skills and knowledge accumulated in carbon-emitting energy infrastructure may constrain regions to diversify and produce complex knowledge in renewable energy technologies. This reasoning leads to the next hypothesis:

H3: Regions located in countries that have historically relied on carbon-emitting energy infrastructure are less likely to develop a portfolio of complex knowledge in renewable energy technologies.

2.3.2 Place dependency

The main argument behind place dependency is that knowledge production is differentiated among locations (Heimeriks & Boschma, 2014). From a smart specialisation perspective, regions differ in terms of their capacities to create new knowledge depending on the strength of their institutional contexts (Morisson & Pattinson, 2020). Because the creation of new knowledge depends on the production and use of tacit knowledge, which is difficult to exchange over long distances (Asheim & Gertler, 2005); knowledge remains unevenly distributed in space (Heimeriks and Balland, 2015; Strambach 2010) and some regions tend to concentrate the production of complex knowledge (Balland et al., 2020). Moreover, regions differ markedly in the number of extra-regional linkages, and consequently they have a different degree of access to complementary knowledge (Balland & Boschma, 2021). In the following sections, these two mechanisms of place dependency in the knowledge production process are introduced in more detail.

2.3.2.1 Knowledge accumulation

It is widely recognized that the accumulation of knowledge is central to innovation and economic performance (Heimeriks & Balland, 2016). However, knowledge production and accumulation remain unevenly distributed across locations (Heimeriks et al., 2019). Likewise, the emergence and growth of renewable energy technologies is strongly shaped by the dynamics of knowledge creation in the geographical space (Kraft et al., 2014). Knowledge development of renewable energy technologies does not occur simultaneously in all countries (Sousa et al., 2014). Typically, some countries lead the production of knew knowledge; while others adopt the technology when it is already being diffused, avoiding the costs associated with early knowledge development and experimentation. Since the production of complex knowledge is unevenly distributed across regions (Pintar and Scherngell, 2018) and the accumulation of tacit knowledge provides an intangible asset that is difficult to copy by non-local agents (Heimeriks et al., 2019), it is expected that the accumulation of knowledge in renewable energy technologies is unevenly distributed as well. In that sense, the capacity of a region to accumulate knowledge provides more opportunities to diversify into more complex technologies (Heimeriks & Balland, 2016). It is therefore expected that the extent to which a region contributes to the knowledge stock of a given technology, will determine the possibilities it has to further develop complex knowledge. This proposition leads to the following hypothesis:

H2. Regions with more accumulated knowledge are more likely to develop a portfolio of complex knowledge in renewable energy technologies.

2.3.2.1 Access to complementary knowledge

Interregional linkages are considered to give regions access to external knowledge that can tackle or avoid the tendency of regions to get locked-in (Balland & Boschma, 2021). The ability of regions to capture and re-use external knowledge is regarded as a fundamental element to sustain and refine the local scientific profile of specialisation and competitiveness (Ascani et al., 2020). In fact, trans-local networks can provide regions with diverse and related information sources and opportunities to develop novel trajectories of specialisation by combining internal and external knowledge resources (Boschma and Iammarino, 2009; Owen-Smith and Powell, 2004). From the innovation systems literature, it is well known that knowledge diffused trough networks has a positive impact on the knowledge creation process (Hekkert et al., 2007). Knowledge diffused trough networks is especially relevant in renewable energy technologies that rely on an analytical knowledge base. In those technologies, knowledge is more likely to be codified and transmitted beyond regional and national borders (Binz & Truffer, 2017). On the other hand, in technologies relying on a synthetic knowledge base, knowledge tends to be spatially sticky, and its transmission remains more limited (Binz & Truffer, 2017). Overall, access to non-local capabilities is important for regional diversification when relevant capabilities are missing (Balland & Boschma, 2021) and regions having more interregional linkages are more likely to access a greater diversity of complementary knowledge. Since knowledge complexity is defined by its high diversity and low ubiquity (Hidalgo & Hausmann, 2009), the following hypothesis is introduced:

H4. Regions that access a greater diversity of complementary knowledge trough interregional networks are more likely to develop complex knowledge in renewable energy technologies; and to a greater extent in technologies relying on a synthetic knowledge base.

3. Methodology

3.1 Research design

This study is based on a repeated quantitative cross sectional research design to explore patterns of complex knowledge production. Various indicators were constructed as a means to operationalise the theoretical framework. By constructing a dataset of relevant indicators, the relationship between knowledge complexity and mechanisms of path and place-dependency was tested by estimating a multiple regression analysis. European regions are the unit of analysis and data was collected for six renewable energy technologies in two non-overlapping periods. Having presented an overview of the data by means of histograms and scatterplots, a multiple regression analysis was estimated. All analysis were conducted using the statistical software R.

3.2 Case description

The European Union represents a relevant case of a region committed to increasing the share of renewable energy trough investment in research and innovation. For this purpose, the European Commission introduced the smart specialisation policy framework to support regional prioritisation in innovative sectors, fields or technologies and more recently to support place-based innovation policies linked to sustainability (S4+). Within this new policy approach, the European Commission intends that smart specialisation strategies contribute to the decarbonisation of energy systems (European Commission, 2019a). In such context, clean energy has become one of the main priorities and two thirds of all regions have given priority to the regional innovation capacities and potential linked to energy transition actions, signifying a direct effect in such decarbonisation (European Commission, 2018). Furthermore, smart specialisation strategies targeting renewable energy technologies are important in Europe for the discovery and usage of localised energy sources, for mobilisation of heterogeneous actor networks around regional 'sustainable energy' visions, and for capitalising on place-based innovation and technology development processes (Steen et al., 2018). In sum, the European Union is an interesting case to study the regional patterns of knowledge production due the more prominent role that place-based innovation policies are having. Especially, smart specialisation policies targeting renewable energy technologies, which can potentially impact the European climate and energy policy targets.

Renewable energy technologies comprise those technologies based on the conversion of energy sources that are regenerative or inexhaustible like solar energy, wind energy, hydropower, geothermal, biomass, tidal and wave energy. Exploring the patterns of complex knowledge production in renewable energy technologies is a very interesting case to look at for a couple of reasons. First, renewable energy technologies are considered more complex and novel than non-green technologies (Barbieri et al., 2020). Second, renewable energy technologies draw knowledge in a greater extent from related technologies (Nemet, 2012) which are more likely to be recombined when they are strongly present in the same region (Boschma, 2017). This means that scientific and technological relatedness plays an important role in facilitating the learning process and creating opportunities to combine related technologies (Li, 2020). In fact, countries move along cumulative paths of specialisation towards more complex technologies (Perruchas et al., 2020). All in all, the unique characteristics of knowledge production in renewable energy technologies makes them an appropriate instance to answer the research questions that motivate this thesis research.

Following the proposed classification of the IEA (2006) scientific publications are collected for renewable energy technologies with different levels of technological maturity. Accordingly, the IEA classifies renewable energy technologies based on both their maturity (IEA, 2006) and their readiness level (IEA, 2020). By combining these classifications, it follows that first-generation technologies have already reached maturity and their growth is more predictable, as is the case of hydropower and geothermal power. Second-generation technologies are undergoing rapid development and they are in commercial operation and some of them need to be integrated at scale, such as solar photovoltaics and wind power. Lastly, third-generation technologies, like concentrated solar power and ocean energy, are presently in different developmental stages: ranging from the outlining of basic scientific principles to the initial stages of building the first commercial demonstrations.

Even though there is not a clear-cut starting point of a single global energy transition, Markard (2018) proposes two phases, in which technologies reach different levels of maturity and diffusion. This distinction is consistent with the IEA technology classification (2006) as it can be seen in Table 1. The beginning of the first phase can be established in 1991, when the first feed-in tariff policy was implemented in Germany. This phase is characterized by the emergence of solar and wind technologies (second-generation technologies). A second phase started to emerge by 2000 depicted by the accelerated diffusion of wind and solar technologies. Following this distinction, scientific publications are collected for the second phase (2000-2019) of the global energy transition. This phase is divided in two non-overlapping periods: 2000-2009 and 2010-2019, in order to capture two different stages of the scientific progress reached by technologies with different levels of maturity.

Table 1. Renewable energy technologies per phase and maturity

Phases of the energy transition	Renewable energy technologies	IEA technological maturity classification
Pre-transition (from the industrial revolution to the end of 19th century)	Hydropower Geothermal power	First-generation
First phase (1991-1999)	Solar photovoltaics (PV) Wind power	Second-generation
Second phase (2000-ongoing)	Concentrated solar power (CSP) Ocean energy (tidal and wave)	Third-generation

3.3 Data collection strategy

Considering that energy is an extensive and multidisciplinary domain of research (Archambault et al., 2009), establishing cognitive boundaries for each technology represents a currently underdeveloped methodological approach. Therefore, two different approaches were combined in order to retrieve the most relevant scientific publications embedded in the knowledge base of a given renewable energy technology. In this section, those methodologies are introduced in more detail.

In this research, scientific publications are used as an indicator for regional knowledge production. While these represent merely a part of the codified knowledge base of a region, they do provide a rich source of information about the local knowledge base that cannot be easily obtained from other sources (Heimeriks & Balland, 2016). More particularly, scientific publications included in patents, serve as an indicator that links the production of knowledge to the technological development (Tijssen et al., 2001). While the references of patents to other patents show the technological context of an invention, literature references reveal the other types of scientific knowledge that were used to either come to the invention or to contextualize the invention (Yang, 2016).

Those references are usually called non-patent literature references which can be either scientific publications, technical standards, conference proceedings, clinical trials, books, manuals, technical or research reports, or any other technical scientific material. They differ from regular academic publications because they do not have an academic purpose, such as supporting a claim, contrasting rival explanations or acknowledging previous research. Instead, these references aim to expose what has already been published and disseminated about the invention in order to justify its novelty (Velayos-Ortega & López-Carreño, 2021). In this thesis, we refer to them as scientific publications, which mainly include journal articles, reviews and proceeding papers (≈ 95% of the sample). The data collection strategy included the following five steps:

1) **Applying the Y02 patent classification system to retrieve scientific publications.**

The Y02 patent classification system is a tagging scheme developed by experienced examiners, which provides additional classification next to the European Patent Classification (ECLA) and the International Patent Classification (IPC) of patent documents related to climate change mitigation technologies. Among the four subgroups of the Y02 scheme, the Y02E comprises the six renewable energy technologies examined in this research. The Table 1 shows the six technology tags, which correspond to each renewable energy technology. By applying a matching string technique, scientific publications were retrieved from the EPO (European Patent Office) Worldwide Patent Statistical Database (PATSTAT) available in the Centre for Science and Technology Studies (CTWS) institute. This database matches scientific publications cited in patents with scientific publications available in the Web of Sciences database. Accordingly, scientific publications were retrieved for each technology for the two non-overlapping periods (t_1 and t_2).

Table 2 Y02 Scheme

Technology	CPC - Y02
Hydro	YO2E 10/20
Geothermal	YO2E 10/10
Solar photovoltaics (PV)	YO2E 10/50
Wind (offshore and onshore)	YO2E 10/70
Solar thermal	YO2E 10/40

Tidal wave ocean	YO2E 10/30

2) Clustering scientific publications.

The retrieved scientific publications were clustered according to a classification of research areas developed by Waltman & van Eck (2012), in which publications are clustered based on citations' relations. Each publication is assigned to a single research area and research areas are organized in hierarchical structure. In this thesis, the lowest level of such classification was used, which entails 4,013 micro clusters comprising all publications in the international scientific literature in a time period that goes from the year 2000 to date. The knowledge base of a given renewable energy technology was captured by taking all the publications classified under its respective code in the Y02 scheme. The clusters of the publications were visualized in the VoS viewer software developed at the CTWS (see Appendix A). VoS viewer crates maps of clusters based on network data in terms of co-citation links. The closer two clusters are located to each other, the stronger their relatedness. The size of the clusters (depicted by circles in the maps) determines its weight, which is given by the number of publications it contains. In order to capture the impact that a given publication has in the knowledge base of a given cluster, its relative weight was calculated by taking the total number of times it was cited by other publications. Appendix A includes the visualization of the clusters that comprise the publications attributed to the knowledge bases of the six technologies.

3) Analysing and filtering clusters

Clusters that only contain one publication were excluded from the sample, as they are not meant to contribute to the knowledge development of the research area. At the most aggregate level of the CTWS classification, publications were clustered in five main fields: social sciences and humanities; biomedical and health sciences; physical sciences and engineering; life and earth sciences; and mathematics and computer sciences. After clustering the scientific publications most of them belonged to both the field of physical sciences and engineering (61%) and the field mathematics and computer sciences (15%). In total, those fields represent 76% out of the total of publications in the six technologies. Exceptionally, some technologies also had a larger share of publications within the field of biomedical and health sciences. However, after manually reviewing the title and abstracts of some publications in such fields, they were not found to directly contribute to the knowledge bases of the technologies. Therefore, those publications were not included in the sample. Lastly, publications from the field of social sciences and humanities were also excluded since their contribution was minimal (0,6%), which supports the assumption that scientific publications cited in patents are more likely to be linked to technological development.

4) Expanding the sample

Even tough, scientific publications cited in patents are understood to contribute to the knowledge development of a given technology, they represent a relative share of the entire scientific knowledge stock. In addition to that, some technologies rely more on an analytical knowledge base than on a synthetic knowledge base, such as hydropower or geothermal energy. For that reason, the sample size of those technologies was very small, and a limited number of European regions fall into the sample. For that reason, a relatedness method based on direct citations was followed to increase the number of publications. It was assumed that such method provided a stronger indication of the relatedness of publications than co-citations or bibliographic coupling (Waltman and van Eck, 2012). By following this technique, publications that either cited or were cited by the sample were included in the final sample.

5) **Selecting publications within European regions for two non-overlapping periods (*t_1* and *t_2*).**

After the sample was increased, publications were attributed to European regions as units of geographical analysis. Each publication contains one or more institutional addresses that enabled me to specify the location of the institutions to which the authors were affiliated. Publications were attributed to each author location and no fractional counting was applied. Lastly, publications were subset in two non-overlapping periods (t_1 and t_2) within a timespan of ten years each (2000-2009 and 2010-2019). By attributing publications to each EU region, it was possible to construct a data frame of regions, clusters, and publications for each technology.

3.4 Operationalisation

In this section, the operationalisation of the theoretical framework is presented. The dependent variable corresponds to the knowledge complexity index calculated for each region in the subfields previously defined for each technology. The indicators designated for each independent variable aim to reflect both path and place dependency of the knowledge production process. Likewise, control variables have a designated indicator as it can be seen in Table 2.

3.4.1 Dependent variable

Knowledge complexity

Usually, patent data is used to calculate a knowledge complexity index (Balland et al., 2018; Balland & Rigby, 2016; Hidalgo & Hausmann, 2009); however, scientific publications cited in the front-page of patents represent an important source of scientific knowledge that is relevant to the knowledge presented in the patent (Tijssen et al., 2000). In fact, science contributes to the technology development as a source of new knowledge which bring ideas for new technological possibilities, engineering design tools and instrumentation (Brooks, 1994). The more scientific papers are cited in patents, the higher their market value (Cassiman et al., 2008; Poege et al., 2019). In this research, scientific publications are used to calculate the complexity of a region's scientific profile in a given technology following the method of reflections proposed by Hidalgo & Hausmann (2009). The calculations of such method were computed with the assistance of the EconGeo package in R (Balland, 2017). Such calculations are explained in more detail in this section.

The KCI is based on the diversity and ubiquity of a region's scientific profile. The scientific profile of a region is depicted by the clusters in which it has a Revealed Comparative Advantage (RCA), that is to say, the clusters in which a region specializes in. Clusters represent specific scientific subfields of a technology, which in turn, aggregate related publications based on the CTWS classification of science. The knowledge base of a given technology is comprised by a set of clusters that represent different scientific subfields of aggerated publications. To construct the KNI for European regions, the regions are considered as the producers of the scientific publications that each cluster contains.

The first step to construct the KNI was to generate an incidence matrix (*I*) based upon which regions have an RCA in a given cluster of publications, which determines the specialization of regions in the scientific area that represents the cluster. If the share of publications counts of region *r* in a given cluster *c* is higher than the share of publications in the entire European Union, such region has an RCA. Mathematically, that condition can be expressed by introducing S_{rc} as the share that a region *r* has in the European stock of clusters *c* and T_c as the total share of clusters within the European regions. The RCA was calculated as a binary variable, where a value of 1 indicates that a region *r* has a greater share of publications in clusters *c* than the average of the European regions. Using this notation, RCA can be written as follows:

$$RCA_{rc} = S_{rc} \,/\, T_c \qquad (1)$$

$$T_c = \sum_r S_{rc} \qquad (2)$$

Having calculated the RCA of every region in every cluster, a region-cluster bipartite network (denoted by *M)* was constructed connecting regions to the clusters in which they have RTA, in which *c* represents the clusters and *r the* regions. By definition, a bipartite network is a set of nodes and links in which nodes can be separated into two groups – regions and clusters in our case – in such a way that links only connect nodes in different partitions. Following Balland and Rigby (2017) we might refer to such bipartite network as the European region-knowledge network of a given technology, which represents the positions of European regions in the knowledge space reflecting the clusters in which they have an RCA. The degree centrality of each region was calculated ($K_{r,0}$) as the number of clusters that a region has an RCA in (3), and the degree centrality of each cluster ($K_{c,0}$) is presented as the aggregative numbers of regions that have RTA in such cluster (4).

$$K_{r,0} = \sum c \;\; M_{r,c} \qquad (3)$$

$$K_{c,0} = \sum r \;\; M_{r,c} \qquad (4)$$

Following the method developed by Hidalgo & Hausmann (2009), the calculation of the KNI scores was achieved by a technique called method of reflections, which combines measures of diversity and ubiquity. This method can be generalized by choosing different values for K_r and K_c and iterating over. Thus, departing from (3) and (4), it follows that the average ubiquity of a region is given by $K_{r,1}$ (5), which denotes the average ubiquity of the scientific profile in which a region has an RCA. In other words, it represents how common the scientific subfields in which a region is specialised. In (6) it is expressed $K_{c,1}$, which denotes the diversity of a region that has RCA in a particular cluster.

$$K_{r,1} = \frac{1}{K_{r,0}} \sum_r M_{r,c} \, K_{c,0} \qquad (5)$$

$$K_{c,1} = \frac{1}{K_{c,0}} \sum_c M_{r,c} \, K_{r,0} \qquad (6)$$

Proceeding with the method of reflections, the next layer $K_{r,2}$ (7) stands for the average ubiquity of the scientific profile in which a region has an RCA. The higher the ubiquity, the greater the number of regions that contribute to the knowledge development of a given scientific subfield. In the same layer, (8) $K_{c,2}$ stands for the ubiquity of a region that has an RCA in a specific cluster. In sum, the more diversified and the less obliquitous a region's scientific profile, the higher its complexity (Hidalgo & Hausman, 2009). Therefore, the KCI of the regions was computed by dividing the average diversity (5) by the average ubiquity (7) of their scientific profiles, as expressed in (9). The higher the diversity and the lower the ubiquity, the higher the complexity score of a regions' scientific profile.

$$K_{r,2} = \frac{1}{K_{r,0}} \sum_c M_{r,c}\, K_{c,1} \qquad (7)$$

$$K_{c,2} = \frac{1}{K_{c,0}} \sum_r M_{r,c}\, K_{r,1} \qquad (8)$$

$$KCI_{region} = \frac{K_{r,1}}{K_{r,2}} \qquad (9)$$

3.4.2 Independent variables

3.4.2.1 Path dependency mechanisms

Scientific relatedness

Scientific relatedness serves as an indicator to measure the degree to which a region's scientific profile either restrains or facilitates the scientific development of a given technology. We follow the method proposed by Boschma et al. (2014a) in order to capture the scientific relatedness between the scientific profile of a region and the knowledge base of a renewable energy technology. The knowledge base of a technology is given by a collection of clusters that contain a set of related publications, whereas the scientific profile of a region is given by the clusters in which it has an RCA. Likewise, clusters of publications are assumed to represent specific scientific subfields that integrate the knowledge base of a given technology. The steps taken to calculate a region's scientific relatedness are explained in more detail as follows. The calculations of this indicator were computed using the EconGeo package in R (Balland, 2017).

First, it is required to measure the scientific relatedness between the subfields, building upon the matrix (*I*) which contains the scientific specialization of regions. The matrix (*I*) was transposed (I^T) and multiplied by itself ($A = I * I^T$). The output resulted in an adjacency matrix (*A*) in which both the rows and the columns correspond to the scientific subfields. By setting its diagonal to zero, the matrix (*A*) displayed the frequency with which each pair of clusters is part of the scientific profile of a region at the same time. Nonetheless, those frequencies cannot straightforwardly be interpreted as giving measure of relatedness due to the so-called size-effect, which means that some subfields co-occur more often with others for the simple reason that these subfields have more occurrences in the first place (Steijn, 2020).

Therefore, the next step was to normalise the co-occurrences following the approach of Steijn (2020). This method is an adapted version of the association strength of van Eck and Waltman (2009) that avoids the overestimation of relatedness between pairs (Steijn, 2020). The formula is expressed in equation (10), where $\varphi_{i,j}$ denotes the total number of times *i* and *j* co-occur in the same scientific profile of a region. With *T* being the total number of occurrences of *i* and *j* respectively, and *n* being the total number of subfields in $T = \sum_{i=1}^{n} occ_i$; it follows that *m* ($m = \frac{\sum_{i=1}^{n} occ_i}{2}$) is half of *T*, as each co-occurrence involves 2 pairs. Accordingly, occ_i and occ_j denote the total number of occurrences of clusters *i* and *j*, where *i* ≠ *j*. After normalizing the relatedness values, they were binarized following the same approach to calculate the RTA. A value of 0 indicates that two clusters co-occur less frequently than the average and are not considered to be related; whereas a value of 1 indicates that two clusters co-occur more frequently than the average and are therefore considered to be related.

$$\varphi_{i,j} = \frac{occ_{ij}}{\left(\frac{occ_i}{T}\frac{occ_j}{T-occ_i}+\frac{occ_j}{T}\frac{occ_i}{T-occ_j}\right)m}, i \neq j \qquad (10)$$

The last step consisted in calculating the relatedness density scores combining the scientific specialization of regions in matrix (I) and the relatedness between scientific subfields in matrix $\varphi_{i,j}$. By following the method applied by Boschma et al. (2010) and Boschma et al. (2014), the relatedness density (11) was computed by summing up the scientific relatedness of subfield *I* to all the subfields found in the scientific profile of the region *r*, divided by the sum of the scientific relatedness of subfield *i* to all other subfield and multiplied by 100 to obtain a percentage lying between 0% and 100%. The relatedness density scores can be interpreted as the percentage of relatedness between a given scientific subfield to all the subfields in which the region has an RCA. A value close to 0% indicates that a given subfield is not related to a region's scientific profile, whereas a value close to 100% indicates a strong relatedness of such subfield to the region's scientific profile. The relatedness density score attributed to a region (mean) *r* was calculated by taking the average of the scores in all scientific subfields. The higher the relatedness density score, the more possibilities that a region specializes in such given technology (Boschma et al., 2010; Boschma et al., 2014).

$$RD_{i,r} = \frac{\sum_{j \in r, j \neq i} \varphi_{ij}}{\sum_{j \neq i} \varphi_{ij}} \times 100 \qquad (11)$$

Technological and infrastructural carbon lock-in

The carbon lock-in effects are measured by considering the physical dimension of the infrastructure required to produce electricity from fossil fuels. Thus, this variable is measured by obtaining the average gigawatts/hours of electricity generated per year by power plants that use fossil fuels. Data was collected in Eurostat based on the simplified energy balance model (European Commission, 2019b) taking the values of the Gross Electricity Production to account for electricity as the primary form of energy. Eurostat uses the Standard International Energy Product Classification (SIEC), which categorises fuels in nine groups, out of which six come from fossil sources (see Appendix H for complete list). Since no regional data was available for the whole-time scope of this research, data was collected annually at the national level and expressed in gigawatts/hour (GWh). To compute the average' share of electricity generated from fossil fuels, data was subset in two periods (2000-2009; 2000-2009). Accordingly, the average values of each fuel were summed to obtain the total average electricity produced. The share of electricity produced from fossil fuels was computed considering the total electricity produced from all types of fuels. The value obtained for each country *c* was equally attributed to all its regions *r*.

3.4.2.2 Place dependency mechanisms

Knowledge accumulation

The knowledge accumulated in each region was computed taking into account the frequency of a given scientific publication being cited in the front-page of patents (aggregative accounts). By taking the frequency of citations, I was able to capture the scientific impact that a given publication has in the knowledge development of a given technology. For example, if a scientific publication attributed to a given cluster was cited 10 times in the front-page of patents, that was the value considered to compute the weight of the cluster. It was therefore assumed that a publication's citation frequency correlates positively with its scientific impact (Hirsch, 2005). When a publication contained more than one institutional address, no fractional counting was applied; instead, publications were attributed to multiple European regions. For example, if a scientific publication had two institutional addresses, within two or more different regions, belonging to either the same or another country, the frequency of such publication was equally allotted to each region. Publications were subset in two non-overlapping periods within a timespan of ten years each (2000-2009 and 2010-2019). The final value attributed to each region *r* was computed by taking the frequency of all publications attributed to such region being cited in the sample of the technology in question.

Access to complementary knowledge

Following the approach of Balland and Boschma (2021), access to complementary knowledge is interpreted as a measure of the potential complementary knowledge that a given region has access to. Linkages that give access to additional capabilities, related to existing local ones, are meant to have a strong impact on regional diversification (Balland and Boschma, 2021), and on knowledge complexity (Balland et al., 2018; Hausmann et al., 2013; Heimeriks et al., 2019; Hidalgo & Hausmann, 2009). Following the approach of Balland and Boschma (2021), this indicator was calculated building upon two variables previously constructed: the scientific specialization of regions (matrix *I*) and the relatedness density ($RD_{i,r}$). The score of the variable access to complementary knowledge trough interregional linkages gives a measure of the relatedness density that can be added in those scientific subfields in which a given region is not specialized. The more co-citation links a region has with other regions, the more relevant the complementary capabilities from those other regions. The four steps taken to compute this indicator are described as follows.

The first step was to determine which scientific subfields *j* are missing in region *r*. The second step entailed determining which regions *s* are specialized in these scientific subfields *j* (RCA >1) that are missing in region *r.* The third step was to sum all relatedness density scores around a scientific subfield *j* for all regions that have a specialization in scientific subfields *j* (RCA >1), in which region *r* is not specialized. This is called relatedness density added, which measures the amount of relatedness density that can potentially be added by other regions. The fourth step was to determine the number of co-citation links a region *r* has with the other regions and multiply it by the relatedness density added. The value obtained in this step represents the total score of access to complementary knowledge for region *r* in technology. The lower its relatedness density and the more a region is connected to other regions, the higher the score of access to complementary knowledge. Therefore, a score of 0 is given when region *r* has a maximum of relatedness density in all scientific subfields *i* (so no need to connect to other regions), and when it has no interregional ties with regions that could potentially add relatedness density to region *r.*

3.4.3 Control variables

In the previous section, the operationalisation of the dependent and independent variables was described. However, there are also other factors that are known to have an impact on the production of complex knowledge. These factors will serve as our control variables and will be discussed in this section.

Level of economic development

Hidalgo & Hausmann (2009) demonstrated that a country's income, measured by Gross Domestic Product (GDP) per capita, is positively correlated with the knowledge embedded in economic complexity. Following this finding, GDP per capita is used as a control variable to account for the effects of level of economic development in each region. Data was collected from Eurostat and the indicator selected was "Real GDP per capita". This indicator is calculated as the ratio of real GDP to the average production of a specific year, and it is expressed in euros per inhabitant. Since no regional data was available for the timespan of the research, annual data was collected per country. Data was subset in two periods (2000-2009; 2010-2019) and the average of each period was calculated. The value computed for a country *c* was equally assigned to all its regions *r*.

Population

By exploring the spatial concentration of economic activities in US metropolitan areas, Balland et al. (2020) found that complex economic activities concentrate disproportionately in large cities, compared to less complex activities. More particularly, they found a positive and strong linear relationship between the urban concentration and the knowledge complexity of scientific fields. The effects of the urban concentration throughout the regions are thus controlled by including the number of inhabitants. Data was collected from Eurostat at the regional NUTS-2 level for each European region. Demographic data was subset in two periods (2000-2009; 2010-2019) and it the average of each period was calculated. The computed value in each period was attributed to the corresponding region *r*.

Renewable energy market

Li et al. (2020) found that low and middle-income countries benefit from domestic markets for renewables in absorbing and utilising international knowledge spillovers so as to develop renewable energy technologies. Likewise, Sousa et al. (2014) found a positive linear relationship between the cumulative number of publications and the cumulative installed capacity of wind power technology worldwide since the early 1990s. Thus, the effects of the technology upscaling in the knowledge production were controlled by the installed capacity of renewable energy technologies. Data was collected annually from Eurostat using the indicator 'Electricity production capacity by main fuel groups and operator'. This indicator reports the national capacities of power plants in megawatts (MW) and it is broken down by type of technology based on the SIEC classification (see Appendix H for complete list).

This classification allows to gather specific values for the six types of technologies analysed in this research. Data was collected in two periods and the value of each period corresponds to the arithmetic average. The share of the installed capacity of a given renewable energy technology was calculated taking into account the total capacities from all other sources. The value obtained for a country *c* was equally assigned to all its regions *r*.

Table 2. Operationalization of the theoretical framework

Category	Concept measured	Indicator	Description	Database
Dependent variable	Knowledge complexity	Knowledge complexity index (KNI) (scores)	The diverse and unique knowledge that a region possesses	WoS
Independent variables : path dependency	Scientific relatedness	Relatedness density (scores)	The degree to which subfields are related to a region's scientific profile.	
	Technological and infrastructural carbon lock-in	Electricity generated from fossil fuels (GWh)	A country's share of GWh of electricity generated from fossil fuel-based power plants.	Eurostat
Independent variables: place dependency	Knowledge accumulation	Frequency of citations in patents	The number of times a scientific publication attributed to a given region was cited in patents.	WoS
	Access to complementary knowledge	Complementary relatedness density multiplied by the number of interregional linkages (Scores)	The complementary relatedness density that can be potentially transmitted through interregional linkages	
Control variables	Level of economic development	GDP per capita (euros)	A country's GDP divided by its population	Eurostat
	Population	Number of inhabitants	The number of inhabitants of each region	
	Renewable energy market	Installed capacity (MW)	A country' share of installed capacity of power plants based on the technology analysed	

3.5 Data overview

This section aims to introduce the data structure as well as some basic association between the variables that are further explored in the results section. A region within the European Union (plus Iceland, Norway, The United Kingdom and Turkey) is the unit of analysis in this study, which represents a territorial entity based on the NUTS-2 classification. Variables were calculated for six technologies and their values were attributed to each unit of analysis (region). Both the response and three independent variables (scientific relatedness, knowledge accumulation, and access to complementary knowledge) were constructed using publication data. As expected, the number of publications gathered per technology was highly skewed due to the different levels of scientific cumulativeness. Table 3 includes the number of clusters as well as the number of publications (citations) included in the final sample. After combining the variables constructed with publication data with the remaining variables, the number of regions analysed decreased. Table 2 also shows the final number of regional units analysed per technology in each period.

Table 3 Number of publications and clusters collected per technology

2000-2009						
Technology	Hydropower	Geothermal power	Solar PV	Wind power	CSP	Ocean energy
Clusters	32	11	644	168	153	34
Publications	6,254	4,609	6,252,527	118,387	79,243	11,946
2010-2019						
Clusters	32	14	649	173	157	36
Publications	19,159	10,712	27,768,584	584,099	294,851	53,384

Table 4 NUTS-2 regions covered

Technology	Hydropower	Geothermal power	Solar PV	Wind power	CSP	Ocean energy
2000-2009	100	67	218	187	188	134
2010-2019	161	122	223	213	214	174

The values calculated for each indicator are continuous, which makes a multiple regression analysis the best fit to test the relationship between the dependent and independent variables (Rubinfeld, 2000). Appendix D includes scatter plots displaying the relationship of the dependent and independent variables. By looking at that those plots, it was possible to infer that some variables, such as scientific relatedness, were more likely to have a linear relationship than others. For other variables, the relationship was more likely to be logarithmic. That was the case for the predictors: knowledge accumulation and complementary interregional linkages.

As a means to detect if multicollinearity was present among the variables, a Pearson correlation coefficient was calculated for each dataset (see Appendix E). As a rule of thumb, a value higher than 0,8 is considered as a sign of multicollinearity between two variables. Having calculated the Pearson correlation coefficient for each pair of variables, multicollinearity was detected between knowledge accumulation and complementary interregional linkages. The strong positive linear relationship between those variables suggests that regions that are more connected to others, are those producing a relatively larger number of publications in the scientific subfields of renewable energy technologies. Because those variables measured different concepts, they were not excluded from the data analysis. Apart from this, no strong signs of strong multicollinearity were found in the remaining variables.

In order to get more useful insights about the data characteristics, histograms showing the distribution of the dependent, independent and control variables were generated (see Appendix C). As expected, some variables showed a relatively higher level of skewness than others. By computing their skewness coefficient, it was possible to estimate a specific value and direction of skew (see Appendix B). As a rule of thumb, if skewness is less than -1 or greater than 1, the distribution is highlight skewed. That was the case for almost all variables, apart from the relatedness density, electricity from fossil fuels and GDP. For this reason, a logarithmic transformation was applied to high skewed variables, as it is further explained in the following section.

3.6 Regression model

This section aims to introduce the multiple regression model and the data transformations achieved to improve its fit. By performing a multiple regression analysis, it was expected to answer the research questions of this study; aiming to identify to extent to which the development of complex knowledge in renewable energy technologies is either constrained or stimulated by mechanisms of path and place-dependency. A multiple regression analysis was the best fit to test the research questions since all the variables have continuous values. To empirically test the research question, I depart from the parameters of the following regression equation:

$$KNI_{e,r,t} = \beta_o + \beta_1 RD_{e,r,t} + \beta_2 CL_{c,t} + +\beta_3 K_{e,r,t} + \beta_4 CK_{c,t} + \beta_5 GDP_{c,t} + \beta_6 P_{r,t} + \beta_7 M_{e,c,t} + \varepsilon \qquad (12)$$

where *KNI* is the score of the knowledge complexity in a given technology *e* attributed to a region *r* in time *e.* β_o is the constant term and β_n is the estimated coefficient measuring how the KNI responds, on average, to a change in the corresponding predictor, holding all other variables constant. The first predictor of the model is *RD,* which denotes the scientific relatedness density in a particular technology *e* attributed to a region *r* in time *t.* Following the same notation parameters, *CL* is the infrastructural and technological carbon lock-in depicted by the share of electricity generated from fossil fuels in a country *c* in time *t*. *K* represents the knowledge accumulation a given technology *e* by region *r* in time *t*. *CK* denotes the complementary knowledge that can be potentially transmitted through interregional linkages in a region *r* of a given technology *e* in time *t*. GDP is the gross domestic product per capita in a country *c* in time *t*. P is the number of inhabitants of a region *r* in time *t*. M is the share of installed capacity available of technology *e* in a country *c* in time *t*. Lastly, ε represents the error term.

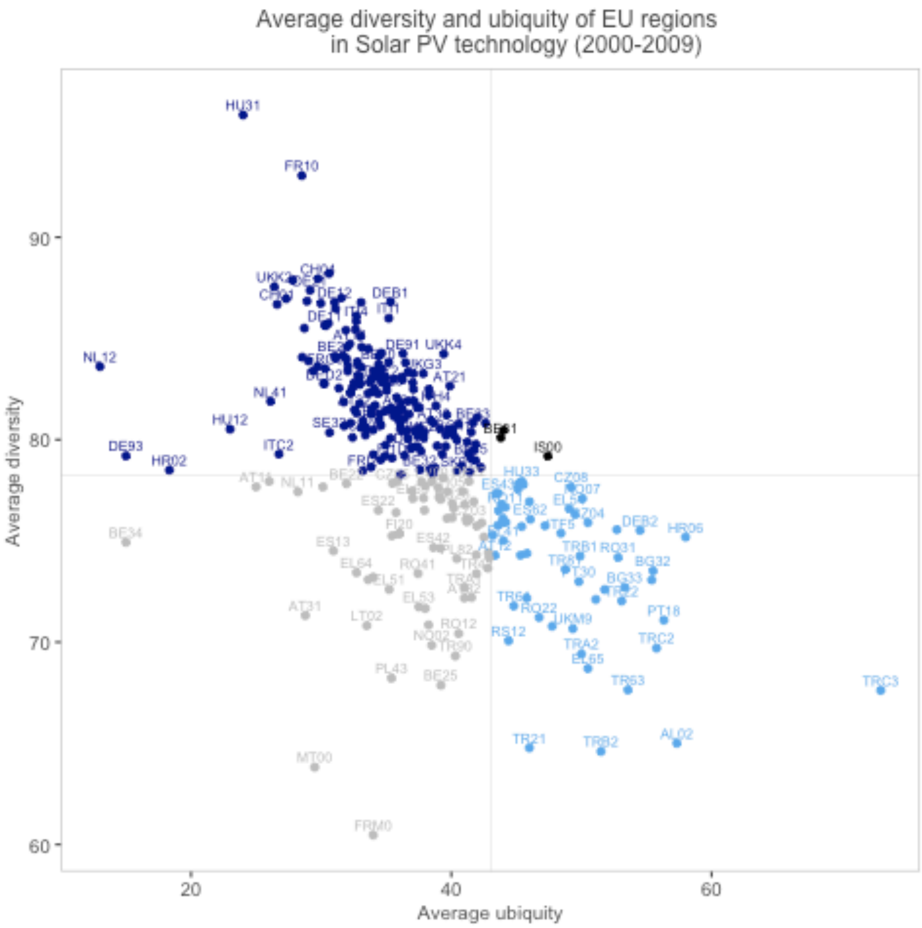
As mentioned in the previous section, some variables included in the regression equation were highly skewed. Thus, having determined their level of skewness, those variables with a coefficient lower than -1 or greater than 1 (at least in 10 cases out 12) were log transformed (see Appendix B). A logarithmic transformation was employed both to simplify the relationship between the dependent and independent variables; and make the distribution of highly skewed variables close to normal (Cohen et al., 2003). By applying this logarithmic transformation, the effect size of skewed variable was overcome (Rodríguez-Barranco et al., 2017). In such transformation, a small constant (+1) was added to those variables containing zeros, in order avoid undefined values (Cohen et al., 2003). However, the values of the variables are still expressed in indifferent units. Therefore, their standard scores were computed with the aim of having comparable coefficients in the regression model. Departing from equation (12) the multiple regression equation containing the transformed variables is the following:

$$\ln{(KNI)_{e,r,t}} = \beta_o + \beta_1 RD_{e,r,t} + \beta_2 CL_{c,t} + \beta_3 \ln{(K_{e,r,t})} + \beta_4 \ln{(CK_{c,t}+1)} + \beta_5 GDP_{c,t} + \beta_6 \ln{(P_{r,t})} + ln\beta_7 \ln{(M_{e,c,t}+1)} + \varepsilon \qquad (13)$$

4. Knowledge complexity of European regions in renewable energy technologies

The knowledge complexity index (KNI) of European regions is given by the degree of diversification and ubiquity of its scientific profile within the knowledge base of a given technology. As an example of a technology having the larger number of observations (218) in the first period of analysis (2000-2009), Figure 1 shows the negative correlation between the ubiquity and diversity of a region's scientific profile. This relationship is in line with the findings of Hidalgo & Hausmann (2009), who demonstrated that regions with higher complexity are those having the higher level of diversity and the lower level of ubiquity. Figure 1 also displays four quadrants that divides regions in terms of their average ubiquity and diversity. Regions with the higher diversity and lower ubiquity are displayed in the left-upper quadrant, whereas regions with lower diversity and higher ubiquity are represented by the light blue dots in the right-lower quadrant. Having calculated the KNI across European regions, the following section introduce the scores obtained, as well as some general characteristic of the knowledge base of each technology. Furthermore, some associations between the KNI scores and the availability of renewable energy sources are given from a spatial perspective.

Figure 1 Quadrants of KNI scores



4.1 Knowledge complexity in hydropower technology

Even tough hydropower is a well-established and mature technology (IEA, 2006), the number of scientific publications cited in patents was relatively low compared to other technologies (see Table 2). A possible reason for this is the strong path dependency and high barriers for radical innovations of large technical systems, such as hydropower (Markard & Truffer, 2006). Likewise, Appendix A shows that the knowledge base of hydropower remains relatively stable during the two periods, which possibly explains the relatively low scientific activity of this technology. The sample of publications collected belongs in its majority to both of the fields of physical sciences and engineering (49%), as well as mathematics and computer sciences (19%). Due to the low number of publications, the KNI score was calculated for only 100 and 161 regions in the first and second period of analysis, respectively.

Figure 2 KNI scores in hydropower technology in Europe

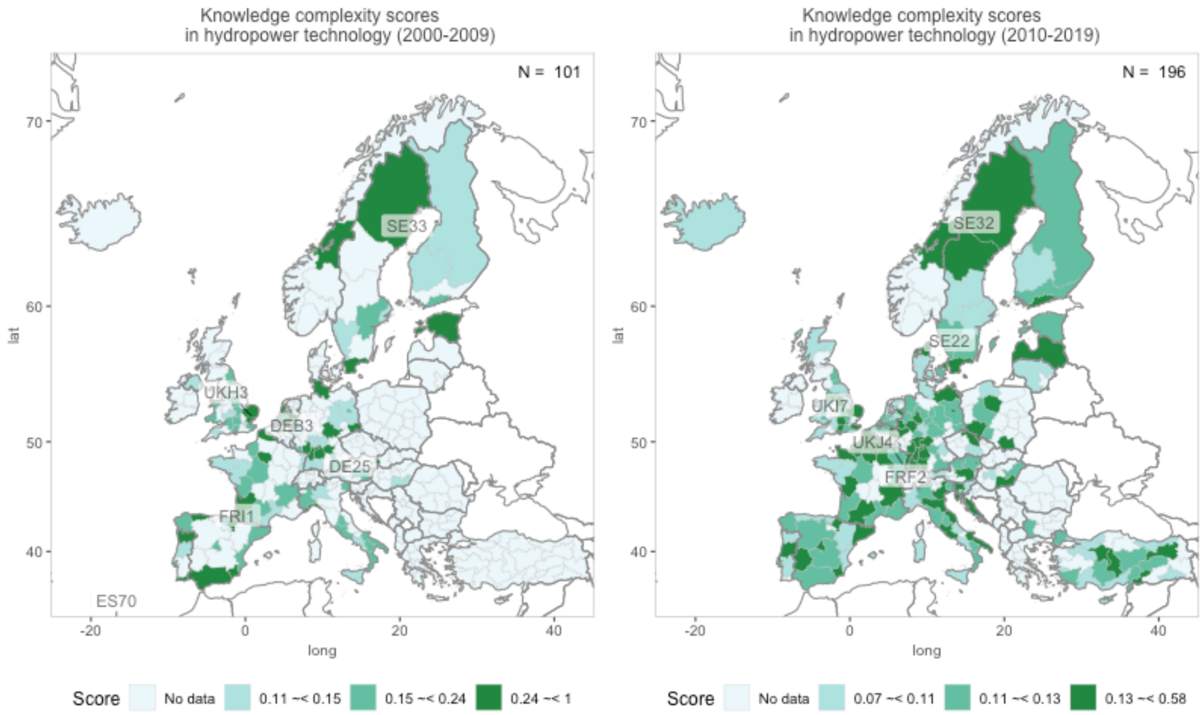


Figure 2 displays the geographical distribution of the KNI scores. The agglomeration of high-scored regions next to each other is noteworthy. This pattern is more visible in the second period, mainly in the north of France, northeast of Italy and west of Germany, possibly due to geographical proximity, which eases the transfer of complex knowledge (Boschma & Martin, 2010). Table 4 shows the top 5 regions with the higher complexity scores. Except for London, it is notorious that top regions are not necessarily large metropolitan areas, instead a combination of small and medium regions can be found as Pintar & Scherngell (2018) also noticed using patent data. Another interesting finding is that top regions do not belong to countries with the largest share of hydropower to produce electricity, such as Norway or Iceland (see Appendix F), which suggests that the development of complex knowledge in hydropower is not related to the availability of resources.

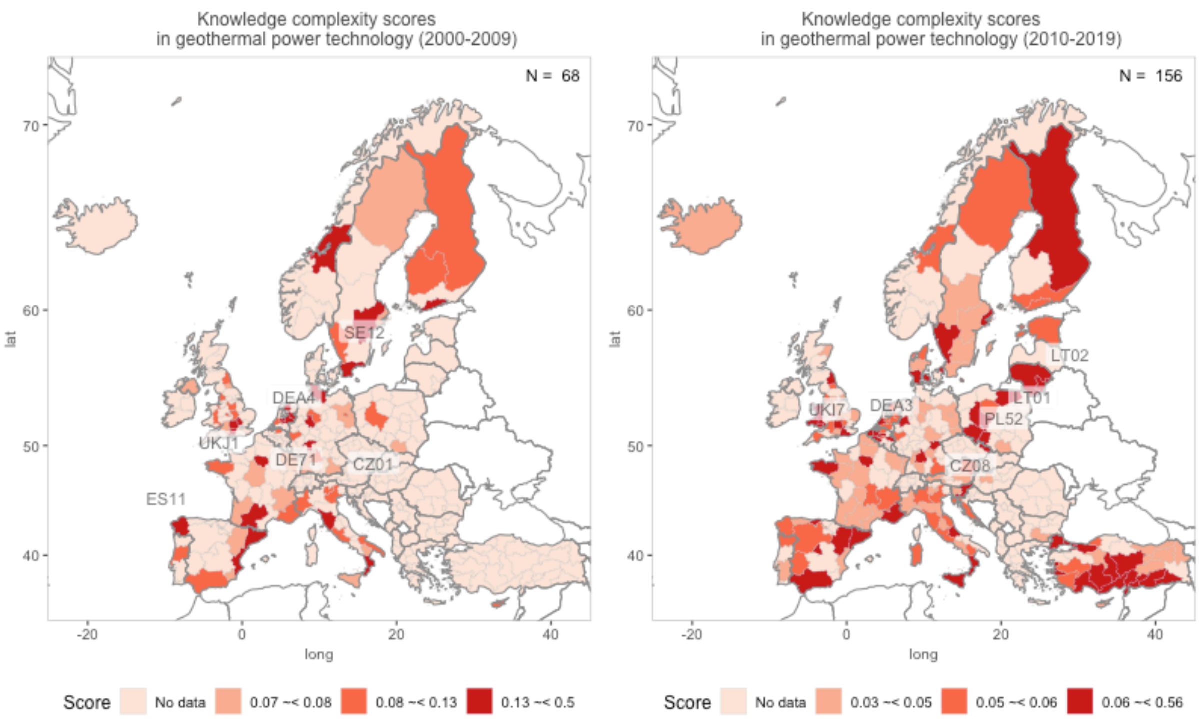
Table 5 KNI scores of top five regions in hydropower technology

	2000-2009			2010-2019		
#	NUT	Region	Score	NUT	Region	Score
1	SE33	Övre Norrland	1.00	UKI7	Outer London - West and North West	0.58
2	DE25	Mittelfranken	0.81	UKJ4	Kent	0.47
3	UKH3	Essex	0.81	FRF2	Champagne-Ardenne	0.38
4	ES70	Canarias	0.69	SE32	Mellersta Norrland	0.36
5	DEB3	Rheinhessen-Pfalz	0.56	SE22	Sydsverige	0.28

4.2 Knowledge complexity in geothermal technology

Geothermal power is considered a mature and reliable technology operating since the beginning of the XX century (IRENA, 2017). Despite its long history, the number of publications linked to patents is relatively low in comparison to other technologies (see Table 2). A possible explanation might be that, large technical systems, like geothermal ones, are characterised by significant barriers for the development and diffusion of radical innovations (Markard & Truffer, 2006). From the cluster analysis, it follows that the knowledge base of geothermal energy is mostly based on publications from the fields of physical sciences and engineering (49%), as well as life and earth sciences (19%). Based on the publications sample, the KNI score was calculated for 68 and 156 regions in the first and second period of analysis, respectively.

Figure 3 KNI scores in geothermal energy technology in Europe



Remarkably, geothermal resources are unevenly distributed in Europe (IEA, 2006) and only a few countries can exploit those resources to produce electricity, mainly Iceland, Italy, Turkey and Portugal (see Appendix F); nonetheless, it is possible to observe in Figure 3, that the spatial distribution of complex knowledge includes not only include regions from countries producing electricity, but from other countries as well. This suggests that, like in the case of hydropower, the availability of geothermal resources does not guarantee the ability of a given region to develop complex knowledge. Also, similar to hydropower, a spatial arrangement of high-scored regions close to each other can be seen, which possibly suggests the existence of spatial spillovers (Pintar & Scherngell, 2018). More specifically, Table 5 displays the top five regions with the highest scores, which include small and medium-size regions.

Table 6 KNI scores of top five regions in geothermal energy technology

	2000-2009			2010-2019		
#	NUT	Region	Score	NUT	Region	Score
1	SE12	Östra Mellansverige	0.50	LT01	Sostines regionas	0.56
2	DEA4	Detmold	0.32	LT02	Vidurio ir vakaru Lietuvos regionas	0.56
3	ES11	Galicia	0.32	CZ08	Moravskoslezsko	0.50
4	CZ01	Praha	0.23	PL52	Opolskie	0.50
5	DE71	Darmstadt	0.23	DEA3	Münster	0.23

4.3 Knowledge complexity in solar photovoltaic (PV) technology

The deployment of solar PV technology started in the early 2000s and after years of technological progress, it is now considered a mature technology (Markard, 2018). Solar PV has, by far, the largest number of publications and clusters (see Table 2). This might confirm that solar PV is an example of a technology that relies on an analytical knowledge base (Huenteler et al., 2016 as cited in Binz & Truffer, 2017) driven by a learning-by-searching mode of knowledge creation (Hekkert et al., 2007). Therefore, the ability of regions to diversify their scientific profile and produce knowledge in non-ubiquitous scientific subfields might be even more relevant for the case of the solar PV technology. Especially in a technology that relies on an analytical knowledge base from a great variety of scientific subfields (clusters) as it can be seen in Appendix (A). The knowledge base of solar PV technology belongs in its greatest part to the field of physical sciences and engineering (87%). Due to the large number of publications, it was possible to compute the KNI scores for 218 and 232 regions for the first and second period respectively.

Figure 4 shows that most high-scored regions are localised in Western and Northern Europe. Either being large metropolitan areas or smaller regions, they tend to cluster together. For example, in both maps, high-scored regions in the south of France, in the north of Italy and in the south of the United Kingdom are cluster together. It is noteworthy that high-score regions belong to countries with different shares of installed capacity, which suggests again that the installed capacity of solar PV technology does not impact in the development of complex knowledge and more predominantly so in high-income countries (Li et al., 2020). For example, The Netherlands includes mostly high-score regions even though the installed capacity of this country is relatively lower than that of other countries, such as Germany or Spain (see Appendix F).

Figure 4 KNI scores in solar PV technology in Europe

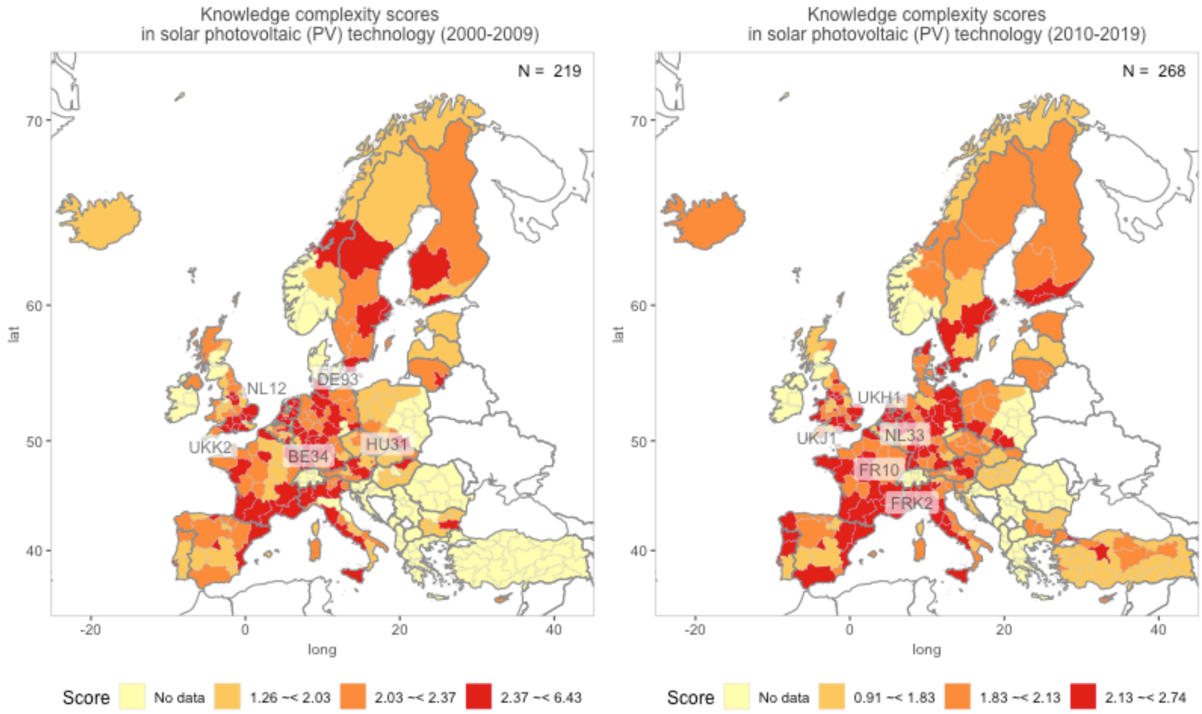


Table 7 KNI scores of top five regions in solar PV technology

	2000-2009			2010-2019		
#	NUT	Region	Score	NUT	Region	Score
1	NL12	Friesland (NL)	6.43	UKJ1	Berkshire, Buckinghamshire and Oxfordshire	2.74
2	DE93	Lüneburg	5.28	UKH1	East Anglia	2.70
3	BE34	Prov. Luxembourg (BE)	5.00	NL33	Zuid-Holland	2.64
4	HU31	Észak-Magyarország	4.00	FR10	Île de France	2.64
5	UKK2	Dorset and Somerset	3.32	FRK2	Rhône-Alpes	2.59

4.4 Knowledge complexity in wind power technology

Together with solar PV, wind power technology has been rapidly deployed since the early 2000s and has reached a certain level of technological maturity as well (Markard, 2018). Despite wind power is considered a technology that relies on a synthetic knowledge base, in which the knowledge embodied is partially codified (Asheim et al., 2011), it has the second largest number of scientific publications. The knowledge base of wind power technology relies on publications from the fields of physical sciences and engineering (53%), as well as mathematics and computer sciences (39%). The sample size of this technology allowed me to compute the KNI scores for 187 and 212 regions in the first and second period respectively.

Figure 5 KNI scores in wind power technology in Europe

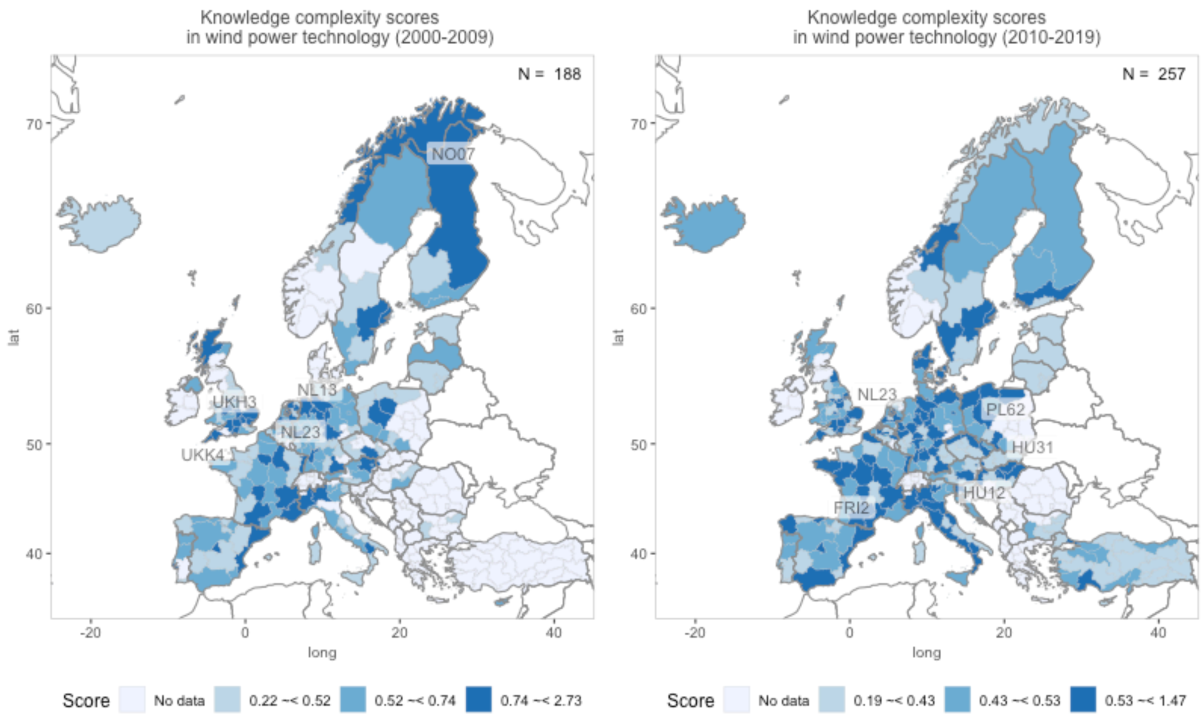


Figure 5 shows the distribution of knowledge complexity in Europe, which is mostly concentrated in Northern and Western countries. Moreover, high-score regions tend to cluster close to each other, suggesting the presence of spatial knowledge spillovers (Pintar & Scherngell, 2018). Similar to solar PV technology, regions belonging to the countries with the largest share of installed capacity, such as Denmark or Spain (see Appendix F), are not necessarily those having the largest scores. Table 7 shows in more detail the top five regions in each period. Whereas in the first period, British and Dutch regions lead the ranking; in the second period, other regions from Poland, France and Hungary catch up.

Table 8 KNI scores of top five regions in solar PV technology

	2000-2009			2010-2019		
#	NUT	Region	Score	NUT	Region	Score
1	UKH3	Essex	2.73	PL62	Warminsko-Mazurskie	1.47
2	NL13	Drenthe	1.90	FRI2	Limousin	1.27
3	NL23	Flevoland	1.83	HU12	Pest	1.21
4	NO07	Nord-Norge	1.61	NL23	Flevoland	0.95
5	UKK4	Devon	1.58	HU31	Észak-Magyarország	0.78

4.5 Knowledge complexity in concentrated solar power (CSP) technology

Concentrated solar power technology is considered a technology still under development and its deployment is more feasible in arid or semi-arid climate, limiting its usefulness to southern Europe (IEA, 2006). Similar to solar PV technology, most of the publications that shape the knowledge base of CSP technology belong to the field of physical sciences an engineering (74%). CPS technology has a relatively large share of publications considering that it is still a technology under development. I was therefore able to calculate the KNI for 153 and 157 regions.

Figure 6 KNI scores in concentrated solar power (CSP) technology in Europe

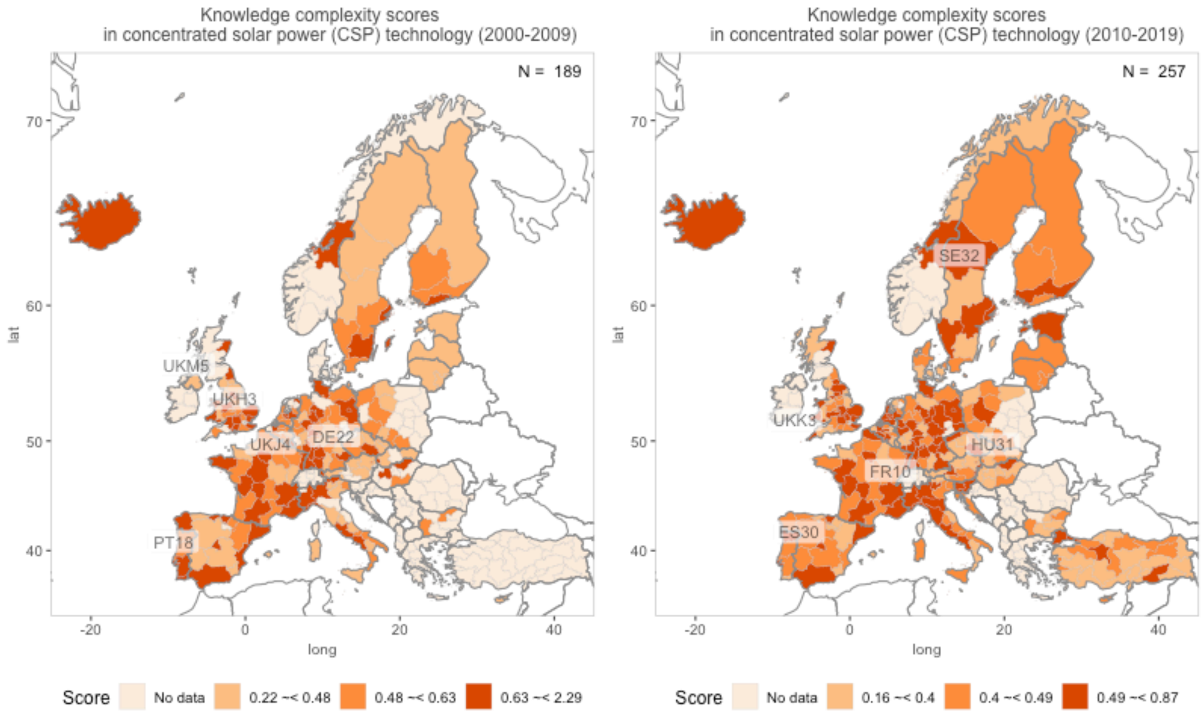


Figure 6 shows the distribution of KNI scores, which is highly conglomerated in some specific areas of Western and Northern Europe. To illustrate, the second maps shows an agglomerating of high-score regions in the north of Italy and east of Germany. Again, regions with the highest score are either localised in countries with the different shares of installed capacity (see Appendix F). More specifically, Table 9 includes the top five regions, which are either large metropolitan areas, such as Île de France and Madrid, or other territories relatively less populated. Similar to previous cases, regions leading in the first period of analysis are not the same of those leading in the second period.

Table 9 KNI scores of top regions in concentrated solar power (CSP) technology

	2000-2009			2010-2019		
#	NUT	Region	Score	NUT	Region	Score
1	PT18	Alentejo	2.29	SE32	Mellersta Norrland	0.87
2	UKJ4	Kent	2.14	FR10	Île de France	0.78
3	DE22	Niederbayern	1.25	ES30	Comunidad de Madrid	0.76
4	UKH3	Essex	1.21	HU31	Észak-Magyarország	0.73
5	UKM5	North Eastern Scotland	1.11	UKK3	Cornwall and Isles of Scilly	0.73

4.6 Knowledge complexity in ocean energy technology

Compared to other renewable sources, ocean energy is considered a technology still under development. However, the number of publications of this technology is even larger than well-established technologies, like hydropower and geothermal power. This is reflected on the relatively low number of publications. The knowledge base of ocean energy technology is based on publications from the field of physical sciences and engineering (56%) as well as from biomedical and health sciences (19%). Based on publications sample, it was possible to calculate the KNI for 134 and 174 regions in the first and second periods respectively. Over the past ten years, several scale projects have been tested in Europe (European Commission, 2021); however, only a few countries have put them in operation; these being only France, Spain and Portugal. By looking at the second map in Figure 7 and at the top regions of Table 9, it is noteworthy that France holds most of the highest-rated regions. This suggests that regions belonging to countries producing electricity from ocean energy are more likely to develop complex knowledge.

Figure 7 KNI scores in ocean energy technology in Europe

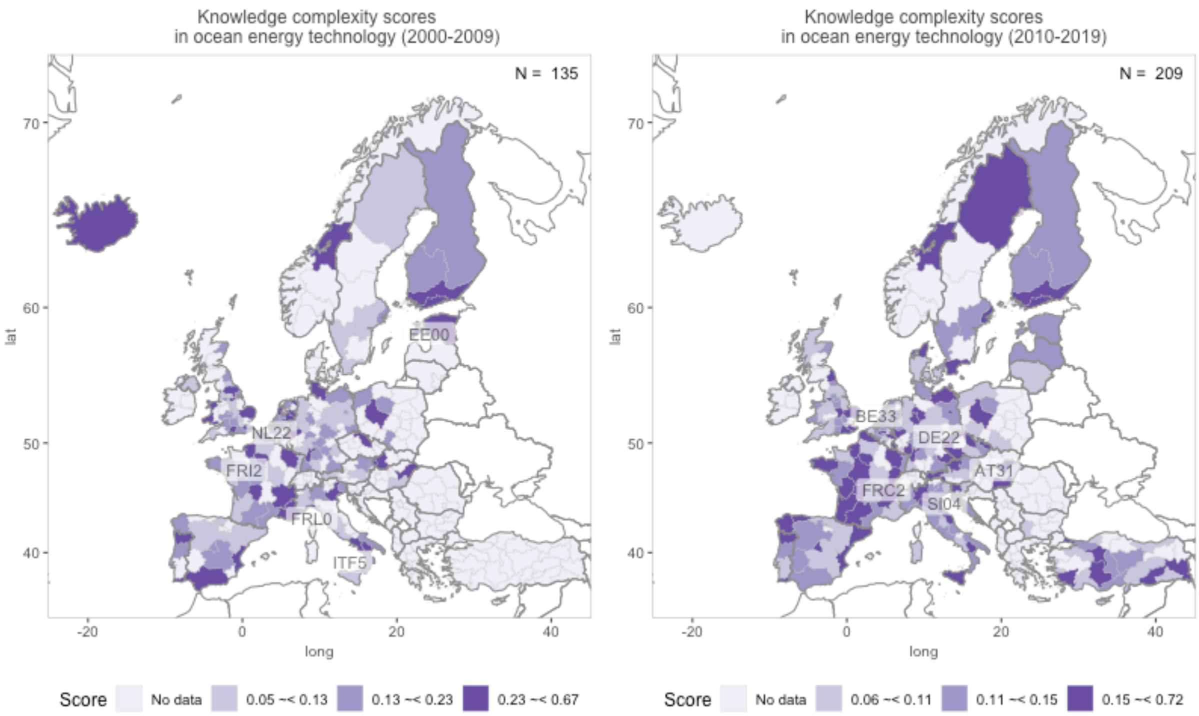


Table 10 KNI scores of top regions in ocean energy technology

	2000-2009			2010-2019		
#	NUT	Region	Score	NUT	Region	Score
1	ITF5	Basilicata	0.67	BE33	Prov. Liège	0.72
2	FRI2	Limousin	0.49	FRC2	Franche-Comté	0.59
3	FRL0	Provence-Alpes-Côte d'Azur	0.48	SI04	Zahodna Slovenija	0.54
4	EE00	Eesti	0.45	AT31	Oberösterreich	0.38
5	NL22	Gelderland	0.42	DE22	Niederbayern	0.38

5. Patterns of complex knowledge production

5.1 Results of the regression analysis

In this section the results of the regression analysis are introduced. The analysis was conducted in six renewable energy technologies in order to identify different patterns of complex knowledge production. The analysis was performed in two non-overlapping periods: 2000-2009 and 2010-2019 to account for the different stages of scientific progress. Since the models include logarithmic transformations, the relationship between the predictors and the independent variables should be interpreted differently. Thus, an absolute variation in the logarithm equals a relative variation in the original variable (Cohen et al.,2003). For example, an increase of one unit in the logarithmically transformed variable is equivalent to multiplying the original variable by the base of its natural logarithm. The following tables show the results of the regression models. The first table (Table 11) includes the results for the first period of analysis and the second table (Table 12) include the results for the second period. Note that the coefficients of the predictor variables can be comparable to each other since the data was previously standardised.

Table 11 Regression results for period 1 (2000-2009)

	Dependent variable:					
	Knowledge complexity					
	Hydropower	Geothermal	Solar photovoltaics	Wind power	Concentrated solar power	Ocean energy
	(1)	(2)	(3)	(4)	(5)	(6)
Scientific relatedness	0.100	0.008	0.352***	0.238**	0.253**	0.274**
	(0.125)	(0.133)	(0.103)	(0.110)	(0.121)	(0.109)
Knowledge accumulation(log)	-0.071	-0.238*	0.303**	-0.046	0.090	-0.192
	(0.126)	(0.137)	(0.141)	(0.123)	(0.145)	(0.122)
Carbon lock-in	-0.071	0.085	0.067	0.161**	0.022	0.185
	(0.123)	(0.147)	(0.062)	(0.074)	(0.073)	(0.123)
Complementary knowledge (log)	0.011	-0.037	-0.443***	-0.109	-0.071	0.050
	(0.118)	(0.142)	(0.121)	(0.096)	(0.113)	(0.107)
GDP	-0.102	0.237	0.258***	0.310***	0.098	-0.120
	(0.113)	(0.156)	(0.068)	(0.081)	(0.079)	(0.096)
Population (log)	-0.161	0.150	0.132	0.135	-0.011	-0.159
	(0.116)	(0.146)	(0.096)	(0.095)	(0.102)	(0.101)
Installed capacity	0.014	-0.081	0.044	-0.122*	0.052	0.210*
	(0.127)	(0.136)	(0.061)	(0.071)	(0.072)	(0.121)
Constant	0.000	0.000	-0.000	0.000	-0.000	-0.000
	(0.101)	(0.121)	(0.058)	(0.068)	(0.070)	(0.085)
Observations	101	68	219	188	189	135
R^2	0.034	0.104	0.278	0.169	0.098	0.086
Adjusted R^2	-0.039	-0.0001	0.254	0.137	0.063	0.035
Residual Std. Error	1.019 (df = 93)	1.000 (df = 60)	0.864 (df = 211)	0.929 (df = 180)	0.968 (df = 181)	0.982 (df = 127)
F Statistic	0.464 (df = 7; 93)	0.999 (df = 7; 60)	11.611*** (df = 7; 211)	5.226*** (df = 7; 180)	2.812*** (df = 7; 181)	1.704 (df = 7; 127)

.01 percent, .05 percent and .1 percent, respectively

*p<0.1; **p<0.05; ***p<0.01

Notes: Carbon lock-in = Technological and infrastructural carbon lock-in (CL); Complementary knowledge = Access to complementary knowldge

Table 12 Regression results for period 2 (2010-2019)

	Dependent variable:					
	Knowledge complexity index (log)					
	Hydropower	Geothermal	Solar photovoltaics	Wind power	Concentrated solar power	Ocean energy
	(1)	(2)	(3)	(4)	(5)	(6)
Scientific relatedness	0.131	0.215**	0.230***	0.422***	0.517***	0.260***
	(0.088)	(0.097)	(0.066)	(0.095)	(0.098)	(0.086)
Knowledge accumulation(log)	-0.062	0.066	0.402**	-0.213**	0.185	-0.043
	(0.094)	(0.102)	(0.166)	(0.104)	(0.112)	(0.096)
Carbon lock-in	-0.194**	0.079	0.093**	-0.029	-0.063	-0.218**
	(0.088)	(0.090)	(0.037)	(0.063)	(0.056)	(0.091)
Complementary knowledge (log)	-0.265***	-0.129	0.143	0.216***	-0.126	-0.262***
	(0.087)	(0.089)	(0.189)	(0.082)	(0.078)	(0.087)
GDP	0.098	-0.212**	0.241***	0.031	0.025	0.064
	(0.088)	(0.097)	(0.041)	(0.074)	(0.062)	(0.078)
Population (log)	0.174**	-0.087	0.080	0.049	-0.016	0.091
	(0.082)	(0.090)	(0.050)	(0.079)	(0.073)	(0.081)
Installed capacity (log)	-0.010	-0.079	-0.028	0.085	-0.029	0.052
	(0.082)	(0.080)	(0.035)	(0.064)	(0.053)	(0.088)
Constant	0.000	-0.000	0.000	-0.000	0.000	0.000
	(0.068)	(0.078)	(0.033)	(0.056)	(0.051)	(0.064)
Observations	196	156	268	257	257	209
R^2	0.115	0.101	0.717	0.229	0.361	0.165
Adjusted R^2	0.082	0.059	0.709	0.208	0.343	0.136
Residual Std. Error	0.958 (df = 188)	0.970 (df = 148)	0.539 (df = 260)	0.890 (df = 249)	0.811 (df = 249)	0.930 (df = 201)
F Statistic	3.496*** (df = 7; 188)	2.378** (df = 7; 148)	94.009*** (df = 7; 260)	10.578*** (df = 7; 249)	20.075*** (df = 7; 249)	5.670*** (df = 7; 201)
.01 percent, .05 percent and .1 percent, respectively						*p<0.1; **p<0.05; ***p<0.01

Notes: Carbon lock-in = Technological and infrastructural carbon lock-in (CL); Complementary knowledge = Access to complementary knowldge

As expected, and apart from hydropower, the coefficient of *scientific relatedness* is significantly positive in all technologies (models 2 to 6), both in the first and second periods of analysis. This suggests that the larger the extent to which the scientific profile of a region is related to the knowledge base of a given technology, the more capabilities a region possesses to develop complex knowledge in renewable energy technologies. For the cases of wind power and the concentrated solar power technologies, scientific relatedness becomes even more significant in the second period of analysis, possibly due to improvements in the scientific specializations of regions in these technologies. These findings indicate that relatedness is an important driver for the knowledge production in renewable energy technologies; (Li, 2020) and regions tend to diversify into new scientific activities that are related to their existing capacities (Balland & Boschma, 2021; Corsatea, 2014). Therefore, the core assumption of path dependency is valid in the case of renewable technologies, which supports hypothesis *H1* of this research, probing that European regions are more likely to develop complex knowledge in technologies related to their scientific profiles.

The coefficient of the predictor *knowledge accumulation* is significantly negative in model 2 of the first period and in model 4 of the second period. This finding suggests that leading regions in the production of scientific knowledge of geothermal and wind power technologies do not necessarily contribute to the development of complex knowledge (see appendix G for leading regions). Nonetheless, another pattern was found in the case of solar PV technology. The significantly positive coefficient (of model 3) in both periods suggests that regions contributing the most in the accumulation of knowledge are more likely to develop a portfolio of complex knowledge. It is very likely that the accumulation of knowledge in solar PV is given by its an analytical knowledge base, which depends on the accumulation of knowledge from a great variety of scientific disciplines (Huenteler et al., 2016 as cited in Binz & Truffer, 2017). This is supported by the relatively large number of publications and clusters from different scientific subfields that were collected during the data collection strategy. Contrary to this, wind power represents an example of a technology that relies on a synthetic knowledge base, in which the knowledge embodied is partially codified (Asheim et al., 2011). Therefore, it is possible that the publications embedded in its knowledge base do not rely on the knowledge accumulated by scientific publications as much as solar PV technology. For the rest of the technologies, this predictor was not significant, therefore, hypothesis H2 cannot be entirely accepted since *knowledge accumulation* cannot be generalised as a driver in the development of complex knowledge in renewable energy technologies.

The effects of the *infrastructural and technological carbon lock-in* as a path dependency mechanism were operationalised as the share of *electricity from fossil fuels*. Table 12 shows that the coefficient of such indicator is significantly positive for geothermal (model 2) and wind power (model 4) technologies only in the first period, whereas they are no longer significant in the second period. On the contrary, the effects of carbon lock-in for solar PV technology (model 3) were only positive and significant in the second period. A different pattern was found in hydropower (model 1) and ocean energy technologies (model 6) during the second period. The significantly negative coefficient indicates that, despite being localised in countries with a greater share of electricity from fossil fuels, regions are able to increase their knowledge complexity in renewable energy technologies. In general, the results show that the constrains of carbon-emitting energy infrastructure have different effects depending on the technology and the period of study. Consequently, they initial hypothesis *H3* cannot be entirely accepted, since it not possible to generalise that, regions located in countries that have historically relied on carbon-emitting energy infrastructure are less likely to develop a portfolio of complex knowledge in renewable energy technologies.

Contrary to what was expected, *access to complementary knowledge* trough interregional linkages has a positive and significant effect for the development of complex knowledge only in geothermal (model 2 of period 1) and wind power (model 4 of period 2) technologies. Another pattern is found in the cases of hydropower (model 1 of period 1) and ocean power (model 6 of period 2) technologies, in which the significant and negative coefficient of such indicator shows that access to complementary knowledge decreases the score of KNI within the regions. As it is not possible to find a positive and significant effect in the majority of the technologies analysed, hypothesis *H4* cannot be accepted for all technologies and therefore it is not possible to generalise that regions that access to a greater diversity of complementary knowledge trough interregional networks are more likely to develop complex knowledge in renewable energy technologies.

In terms of explanatory power, the adjusted R^2 gives a percentage of variation explained by the independent variables that affect the dependent variable. By comparing the R^2 value of the models in the first period, models 3 and 2 have the best fit, which might indicate that the development of complex knowledge in solar PV and geothermal energy technologies, is strongly shaped by changes in the predictor variables. Especially, those variables having the largest coefficients. For the case of geothermal energy (model 2), *knowledge accumulation*, *scientific relatedness* are the variables that contribute the most to the model fit. For solar PV technology (model 3), *access to complementary knowledge*, *scientific relatedness* and *knowledge accumulation* are the variables with the largest coefficient. In the second period, models 3 and 5 have the best fit. For solar PV technology (model 3) *knowledge accumulation* and *scientific relatedness* contribute the most to the fit: whereas in the case of concentrated solar power technology, *scientific relatedness* explains most of the changes.

6. Discussion

In this section, the previous results are interpreted in the context of the theoretical approach of this research. Furthermore, the contributions, limitations and recommendations for future research are given. To conclude, I discuss the policy implications of this research in the context of the smart specialisation strategy policy framework.

6.1 Theoretical implications

This research explored the patterns of complex knowledge production in the context of the European energy transition. Building upon the theoretical foundations of Evolutionary Economic Geography and Smart Specialisation literature, the development of complex knowledge was analysed bringing a regional and temporal perspective. This study was conducted during the so-called second phase of the energy transition, which was split in two non-overlapping periods: 2000-2009 and 2010-2019. The knowledge development in renewable energy technologies was an interesting case to look at, as green technologies are clean energy has become one of the main prairies of European regions implementing smart specialisation strategies.

By visualising the spatial arrangement of KNI scores, a highly heterogenous distribution across Europe was found, in which only a few regions, mainly from the West and North, produce the most complex knowledge, in line with the findings of Heimeriks et al. (2019). This finding is also consistent with the work of Balland & Rigby (2016), which suggests that complex knowledge is more sticky and spatially concentrated than more ubiquitous knowledge. In addition to that, it is very likely that the agglomeration of high-scored regions next to each other suggests the existence of spatial spillovers, as Pintar & Scherngell (2018) suggest. This supports the notion of geographical proximity as a driver for innovation and effective learning, which requires face-to-face interactions (Boschma & Frenken, 2010). In that regard, Glükler (2010) suggests that the more complex knowledge becomes in a particular industry, the more industries do agglomerate. Similarly, Steen et al. (2019) found that region-specific clusters are important for the development of renewable energy technologies and industrial capacity. Besides that, and consistent with the results of Pintar & Scherngell (2018), the highest KNI scores are dispersed across a mixture of small, medium and large regions. This possibly suggests that European regions follow a pattern different from that of cities in the United States, where only a few large metropolitan areas produce the most complex technologies (Balland & Rigby, 2016). Whereas the European ranking tends to be more dynamic and heterogenous, Balland & Rigby (2016) found a more considerable rank stability among large cities in the United States. Overall, a different pattern of spatial and temporal distribution was found in European regions in comparison to other studies exploring the patterns of knowledge production in the United States.

With the exception of hydropower, scientific relatedness was found to be the most important driver in the process of complex knowledge production. It is therefore possible to assume that path dependency has a strong impact on the scientific specialization of European regions among renewable energy technologies. This is consistent with previous studies (Boschma et al., 2014a; Boschma et al., 2014b; Balland et al., 2017; Heimeriks et al., 2019; Li, 2020), which demonstrate that regions are more likely to diversify into more complex technologies if they rely on their existing local related capabilities. Thus, this finding demonstrates that path dependency is still a relevant theoretical concept to explain the formation of technological trajectories driven by the specialization of regions within a set of scientific subfields or technologies. Furthermore, it is possible to confirm that the existing portfolio of regions offers opportunities for related diversification and discourages the creation of knowledge in scientific subfields unrelated to the local knowledge base (Heimeriks et al., 2019). Especially for renewable energy technologies, which are considered complex technologies that require knowledge from a diverse range of scientific disciplines (Barbieri et al., 2020). Overall, these findings demonstrate that path dependency is a relevant theoretical concept to explain the formation of technological trajectories driven by the ability of regions to diversify into new complex technologies.

Regarding the effects of the carbon lock-in, the results suggest that the infrastructure built around fossil fuel technologies, partially limits the development of complex knowledge in three technologies: geothermal, wind power and solar PV. This was not the case, however, for the remaining technologies, in which the regression coefficient was either significantly negative or not significant et all. The significantly negative effects might suggest that the past knowledge accumulated in fossil fuels has a minor impact on current innovation activities in renewable energy technologies as Noally & Smeets (2013) found. Regarding the insignificant effects, Seto et al. (2016) suggest that the ability to break out the infrastructural and technological lock-in depends on the anticipated technological and economic viability and lifetimes of the systems and the costs of moving away from those systems. In that sense, it is very likely that European countries have been able to escape the infrastructural and technological lock-in trough aggressive policies that shift the balance toward new low-carbon technologies assuring its technological an economic viability. Nonetheless, the specific contexts and policies that have possibly opened up new paths for the knowledge deployment of low-carbon technologies go beyond the scope of this research. Overall, it seems that infrastructure and knowledge accumulated around fossil-fuelled technologies does not necessarily generate a lock-in when it comes to the complex knowledge production in renewable energy technologies.

The findings show that for the most part of the technologies, the development of complex knowledge is not highly correlated with knowledge accumulation. This pattern is consistent with the work of Pintar & Scherngell (2018), who found a negative correlation between the rate of patenting and complex knowledge production in European regions. Interestingly, previous studies have found a different pattern in urban areas of the United States. To illustrate, Balland et al. (2020) found that the spatial concentration of productive activities in large metropolitan areas of the United States increases with their complexity. In this research, this pattern was found only for solar PV technology, suggesting that the larger the number of scientific publications with which a region contributes, the more complex the knowledge that is produced. This finding, however, is consistent with Persoon et al. (2021) who found that solar PV technology has a high analytical knowledge base in comparison to other renewable energy technologies by counting the number of scientific references in patents as well as the number of patents filled by universities. Because the accumulation of scientific knowledge is important for solar PV technology, the findings suggest that regions producing more scientific publications are more likely to develop complex knowledge in such specific technology, in line with the findings of Persoon et al., 2021.

The last predictor, access to complementary knowledge trough interregional linkages, revealed a significantly positive relationship only for the case of geothermal technology and wind power. However, for the rest of the technologies it was either negatively significant or not significant et all. This might indicate that the development of complex knowledge in renewable energy technologies relies more on local capabilities than on external resources. This finding is in line with Glücker (2010), who suggests that while the transmission of complex knowledge entails more problems of accurate interpretation; spatial proximities ease transfer and lock out remote actors from the knowledge flows. Thus, for the case of renewable energy technologies, it is very likely that geographical proximity plays a more important role in the knowledge development process than the access to external knowledge and capabilities. In addition, this finding suggests that complex knowledge in the domain of renewable energy technologies has a higher degree of tacitness associated with its value and quality in terms of accessibility and mobility in the geographical space (Pintar & Scherngell, 2018).

6.2 Contributions, limitations, and recommendations for future research

Methodologically speaking, the contributions of this research are twofold. First, previous studies (Balland et al., 2019; Pinar & Scherngell, 2018; Vlčková et al., 2018) have usually operationalised the knowledge complexity concept (Hidalgo and Hausmann, 2009) from a comprehensive perspective (considering all the scientific or technological domains); however, this thesis represents an initial approach to construct a KNI targeting the knowledge base of specific technologies. For this purpose, an innovative methodological approach was developed to obtain a representation of the body of knowledge of a given technology by following the Y02 patent classification scheme and building upon a micro cluster classification developed at CTWS. This methodological approach allowed to establish the cognitive limits of the knowledge base of a technology, avoiding the selection of keywords on a discretional manner. Secondly, this research represents a first attempt to provide a measure of knowledge complexity based on micro clusters of publications cited in patents. By collecting scientific publications cited in patents, it was possible to obtain a better representation of applied knowledge linked to technological innovations. Overall, this methodology facilitated the construction of a KNI based on large data sets, so that it remained as valid and reliable as possible, as a measure of diversity and uniqueness.

In terms of theoretical contributions, this research provided further empirical evidence for the theoretical framework and brought new insights into it. To start with, this thesis proved that path dependency is an important theoretical concept to understand knowledge the production process at regional level. The findings of this research demonstrated that scientific relatedness, as a special case of path dependency, is an important driver to produce complex knowledge in renewable energy technologies. In doing so, it was demonstrated that core assumption of relatedness can be extrapolated to other scientific, technological and economic sectors. This research also constitutes an initial attempt to operationalise the effects of the infrastructural and technological carbon lock-in on the knowledge development process. Even tough, more empirical evidence is needed and as well as the institutional and behavioural lock-in should be taken into consideration (Seto et al., 2016), this study demonstrates that carbon lock-in is no longer a factor limiting the complex knowledge development in renewable energy technologies in Europe. Second, this thesis found new insights into the role that place dependency mechanisms play in knowledge production. It was expected that the accumulation of knowledge, as a special case of place dependency, strongly correlates with the capacity of a region to generate complex knowledge. However, in this study it was found that such correlation is technology-specific. It was found that the accumulation of knowledge is only relevant for technologies with a high degree of analyticity, such as solar PV. Another case of place dependency that was operationalised was the access of regions to intraregional linkages. Previous research states that regions can benefit from them as they are more likely to access to complementary knowledge. However, in this research we found a different pattern. Apparently, the more complex the knowledge, the more geographically-constrained and the less relevant extra regional linkages become. Yet more empirical evidence is required, this finding was supported by the spatial agglomeration of high-score regions next to each other. Lastly, this thesis also contributes to the Smart Specialisation literature by proving empirical evidence of the importance of related diversification. This research demonstrated that European regions are more likely to be successful when diversified into new sectors, activities or technologies related to their local capabilities.

While conducting this research, some limitations emerged. First, the delineation of the knowledge base of the technologies was constructed using scientific publications cited in patents, nonetheless, it might be the case that other relevant scientific publications not cited in patents are left outside the sample. Therefore, the set of gathered publications does not necessarily represent the entire knowledge base of the technologies analysed. Especially, for those technologies with a relatively lower rate of patenting, such as hydropower and geothermal energy technology. Another limitation has to do with the level of aggregation in the Eurostat databases. Energy statistics are usually reported at country level; therefore, it was not possible to get a more detailed overview of the regional energy context. Similarly, GDP was available at regional level only for the second period of the study, thus, national indicator was chosen for both periods. For this reason, the values obtained at national level were evenly assigned to each region.

Additionally, this research did not look at the role of formal and informal institutions that shape the knowledge creation process at regional level. Weak institutions, such as low quality of governance or bonding social impact could have a negative influence on the diversification opportunities of regions (Cortinovis et al., 2017; Rodríguez-Pose & Di Cataldo, 2015). On the contrary, strong institutions foster open knowledge architecture, absorptive capacity and connection to pools of knowledge generated elsewhere (Asheim & Coenen 2005; Bathelt et al., 2004; Cohen & Levinthal 1990). Therefore, even when this study demonstrates that the regional scientific capabilities matter for the creation of complex knowledge, there might be other institutional drivers of great relevance. In the same line of thought, institutions, and behavioural norms, along with technologies and supporting infrastructure, also contribute to the carbon lock-in (Seto et al., 2016) and possibly have implications for innovative activities in low-carbon energy technologies, that were not taken into account in this research.

With these limitations in mind, this study opens up opportunities for future research. First, a lack of understanding of the regional institutional context has been identified as a common issue that regions face when drafting their regional innovation strategies (Morisson & Pattinson, 2020). Because smart specialisation strategies are applied in different regional contexts, it is important to understand what specific institutional features might influence the success of smart specialisation strategies (Grillitsch, 2015). Especially, when smart specialisation strategies are implemented in the context of rigid sectors such as energy, where there are often strong vested interests of the industry and of political actors that seek to influence the institutional environment (Seto et al., 2016; Steen et al., 2019). Likewise, smart specialisation strategies are also likely to be influenced by national institutional frameworks, such as centrality of government, levels of regional autonomy or regional endowments (Steen et al., 2019). Thus, future research could focus on the influence of both regional and national institutional frameworks, as it is still unclear to the extent to which they do influence the design and implementation of individual smart specialisation strategies targeting clean energy technologies.

Although this research showed that the technological and infrastructural carbon lock-in does not have significant effects in the knowledge production of renewable energy technologies; an open question still remains regarding the effects of the institutional and behavioural carbon lock-in when developing knowledge in clean energy technologies. Even though a few studies have conducted research in such regard, they show different results. On the one hand, Santoallha & Boschma (2021) found that the presence of 'dirty' technologies hampers the development of new green technological specialisation. On the other hand, Noailly & Smeets (2013) found that the past accumulated knowledge stock in fossil-fuel technologies has a positive, yet minor, impact on current innovation in renewable energy technologies. This existing paradox in carbon lock-in literature requires more research to find out the extent to which the specialisation of a region in fossil fuel technologies inhibits its innovative activities in clean energy technologies. In particular, this topic is relevant for smart specialisation strategies aiming to foster structural change in making energy systems more sustainable.

6.3 Policy implications

Over the last years, most regions of Europe have developed smart specialisation strategies with the ultimate goal of boosting economic growth and creating jobs and more recently achieving mission-oriented goals, mainly, sustainability and inclusive growth (McCann & Soete, 2020). This shift in policy creates a window of opportunity for smart specialisation in renewable energy technologies. Within this context, this research has some policy implications for this new shift in the rationale of the smart specialisation policy framework.

To start with, this study demonstrates that knowledge complexity can be used as a methodological tool to reveal the strengths and capabilities of a region's scientific profile in terms of their uniqueness and diversity within the knowledge base of a given technology. More particularly, by constructing a measure of knowledge complexity using scientific publications cited in patents, it is possible to capture the role that scientific knowledge plays in technological development. Because patents that cite a larger number of scientific publications are more likely to generate more economic value (Cassiman et al., 2008; Poege et al., 2019), this complexity measure is relevant for smart specialisation strategies aiming to generate knowledge about the future economic value of a structural change, such as the sustainable energy transition (Foray et al., 2011). Thus, this approach can be used to inform policy makers about which the most promising knowledge domains are, in terms of their intrinsic market potential. Indeed, other studies also suggest that knowledge complexity could be used as a methodological tool for selecting prospective industries in smart specialisation strategies (Vlčková et al., 2018).

Secondly, the concept of relatedness is being increasingly highly regarded as relevant for smart specialisation strategies (Boschma, 2017). This concept is supported by previous studies which demonstrate that regions are more likely to diversify into new activities related to their existing scientific profile. (Boschma, 2017). 2019; Heimeriks et al., 2019). Similarly, Santhoalla & Boschma (2020) found that relatedness determines the ability of regions to diversify into green technologies. Consistent with those studies, this research provides further empirical evidence of the importance of related diversification as a key driver for smart specialisation targeting renewable energy technologies. Indeed, it has been demonstrated that diversifying into more complex technologies is difficult for many regions, although it is easier when they are closely related to the existing scientific profile (Balland et al., 2019). In practical terms, this implies that stakeholders need to reflect on the strengths and potentials of a region's knowledge assets during the entrepreneurial discovery process. For instance, a mapping exercise of the scientific and technological profile of a region could be helpful to identify potential domains of prioritisation.

7. Conclusions

Building upon the theoretical foundations of Evolutionary Economic Geography and Smart Specialisation literature, the aim of this research was to determine the extent to which mechanism of path and place dependency influence the capacity of European regions in developing complex knowledge around renewable energy technologies. Thus, this research attempted to answer the following core research question: What are the regional patterns of complex knowledge production in renewable energy technologies?

In order to answer this question, a knowledge complexity index was built based on scientific publications cited in patents of renewable energy technologies. For this purpose, scientific publications were gathered to delineate the knowledge base of the technologies. In doing so, solar PV was found to be by far the technology with the larger number of publications; possibly due to the high level of analyticity of its knowledge base. On the contrary, for well-established and mature technologies, like geothermal and hydropower, the number of publications was surprisingly low; suggesting a low level of analyticity. Once computed, KNI scores were visualised to obtain a perspective on their spatial distribution in Europe. Accordingly, it was found that for the most part of the technologies, high-score regions tend to cluster next to each other, suggesting the importance of geographical proximity as a relevant driver for developing and sharing complex knowledge. Another interesting finding is that high scores are distributed across small-to-large metropolitan areas, suggesting that, regardless of their demographic characteristics, European regions are able to develop high-quality knowledge.

As a second step, a multiple regression analysis was estimated to test the relationship between knowledge complexity and four mechanisms of path and place dependency in the knowledge production process. The results revealed that scientific relatedness, as a mechanism of path-dependency, is the most important driver for the creation of complex knowledge in five out of six models. Based on this finding, it was possible to accept hypothesis *H1*, which holds that that the likelihood of a region to produce complex knowledge relies, to a great extent, on the relatedness between their scientific profile and the knowledge base of the technology in question.

On the other hand, the results indicated that hypotheses *H2*, *H3* and *H4* can be neither entirely accepted nor rejected; suggesting that the effects of path and place-dependency mechanisms in the knowledge production process are technology-specific. Thus, hypothesis 2 was accepted only for solar PV technology, stressing the importance of scientific knowledge for technologies relying on an analytical knowledge base. Hypothesis 3 was rejected in almost all the technologies, meaning that specialised skills and knowledge accumulated around fossil fuel technologies apparently do not hamper the creation of complex knowledge. Similarly, hypothesis 4 was rejected in almost all cases, demonstrating that access to complementary knowledge does not necessarily mean that regions are more likely to diversify their scientific profile and develop more complex knowledge; instead, it appears that geographical proximity plays a more important role in the creation and diffusion of knowledge.

From a smart specialisation perspective, these findings confirm the importance of relatedness as a driver for regional diversification. It was proved that diversifying into related activities yields better results than diversifying into non-related activities, as regions are more likely to develop knowledge with more complexity, which is more valuable and provides a greater competitive advantage. Thus, both knowledge complexity and relatedness can be regarded as useful methodological tools for selecting promising activities. Especially, the use of scientific publications cited in patents allows to capture the future market value of specific technologies.

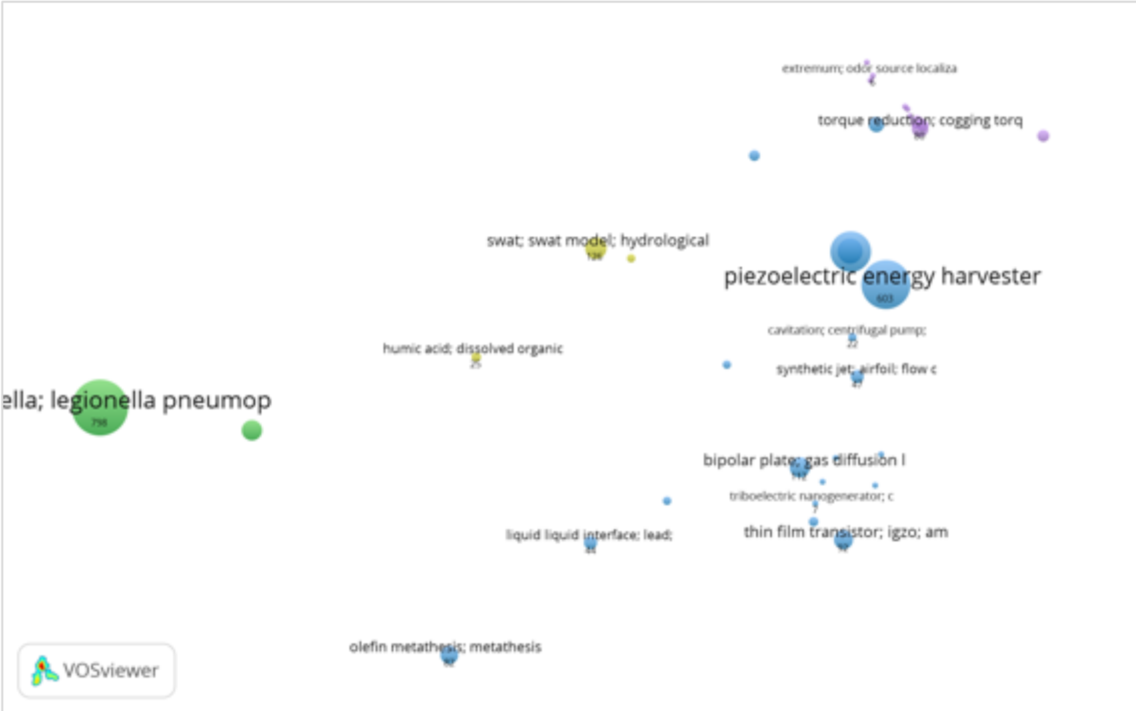
Overall, it can be concluded that European regions implementing smart specialisation strategies targeting renewable energy technologies, must build upon the scientific areas in which they are most competitive. As regions diversify into related fields or activities, they become more likely to develop more complex knowledge around renewable energy technologies, regardless of their capacity to contribute to the knowledge stock or the knowledge and specialised skills accumulated in fossil technologies. By prioritising related activities, regions are more likely to accelerate the uptake of renewable energy technologies, while contributing to the climate and energy goals of the European Union.

8. Appendices

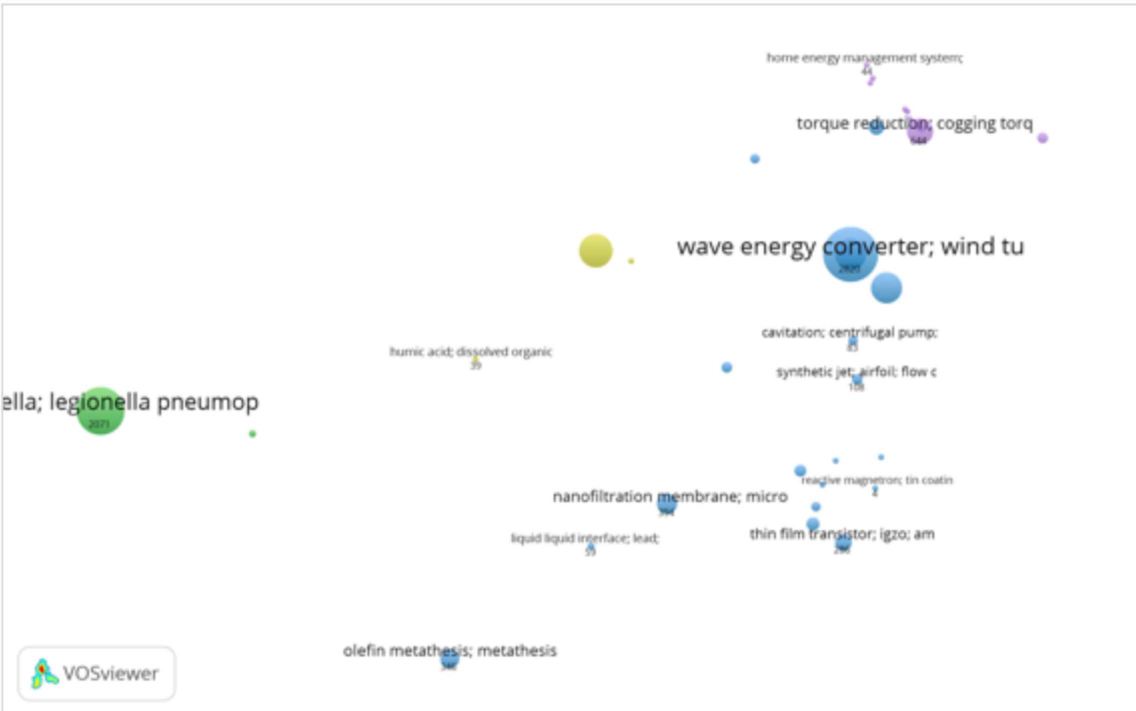
Appendix A. Knowledge bases of renewable energy technologies

A.1 Hydropower

2000-2009



2010-2019



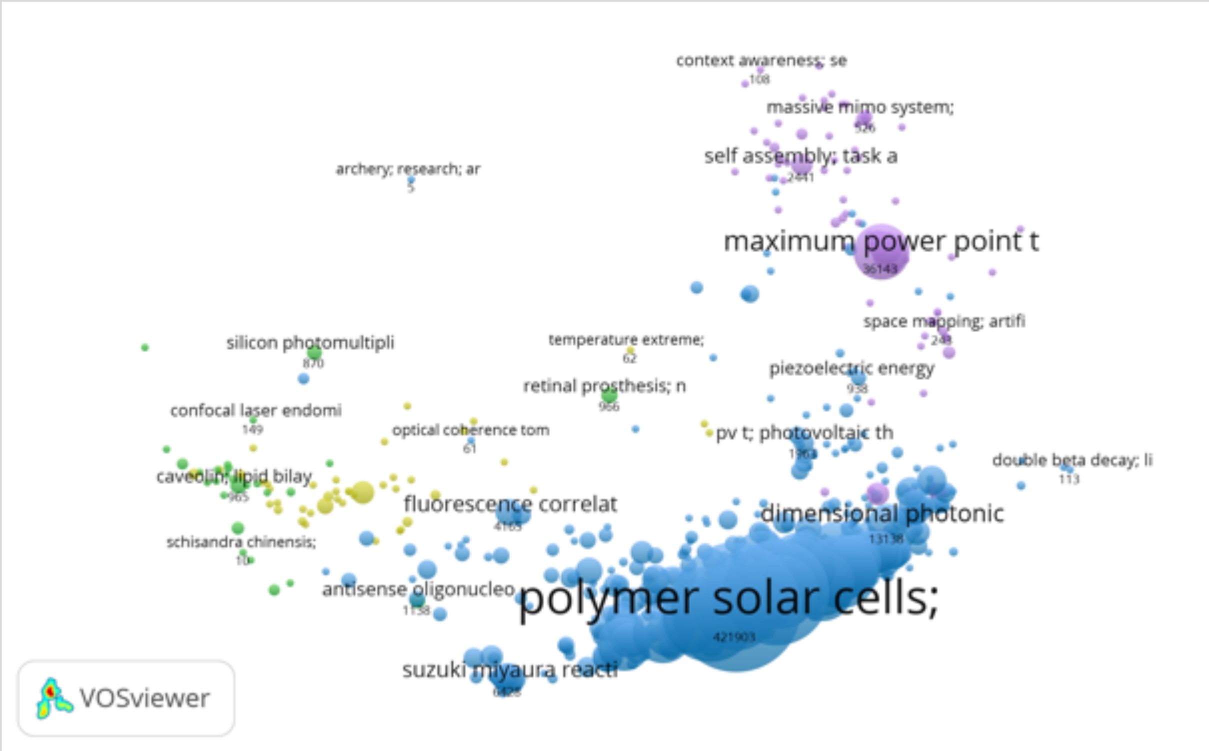
A.2 Geothermal power

2000-2009

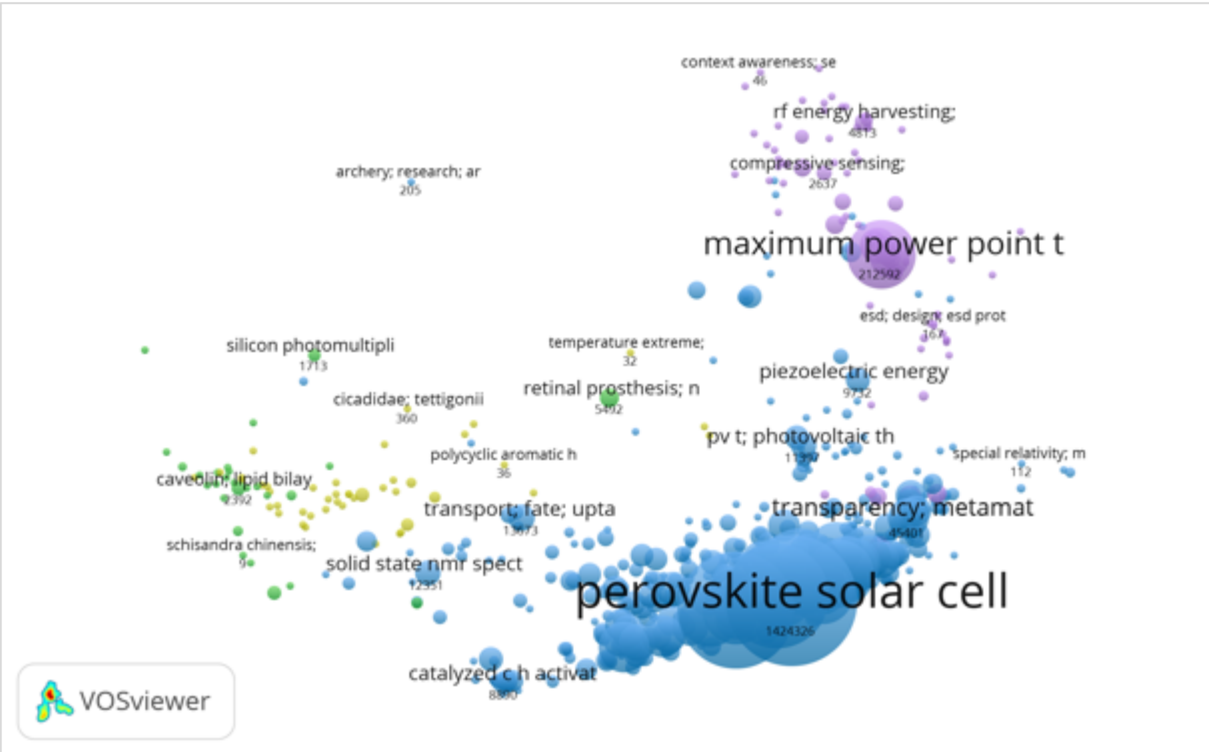
2010-2019

A.3 Solar photovoltaics (PV)

2000-2009

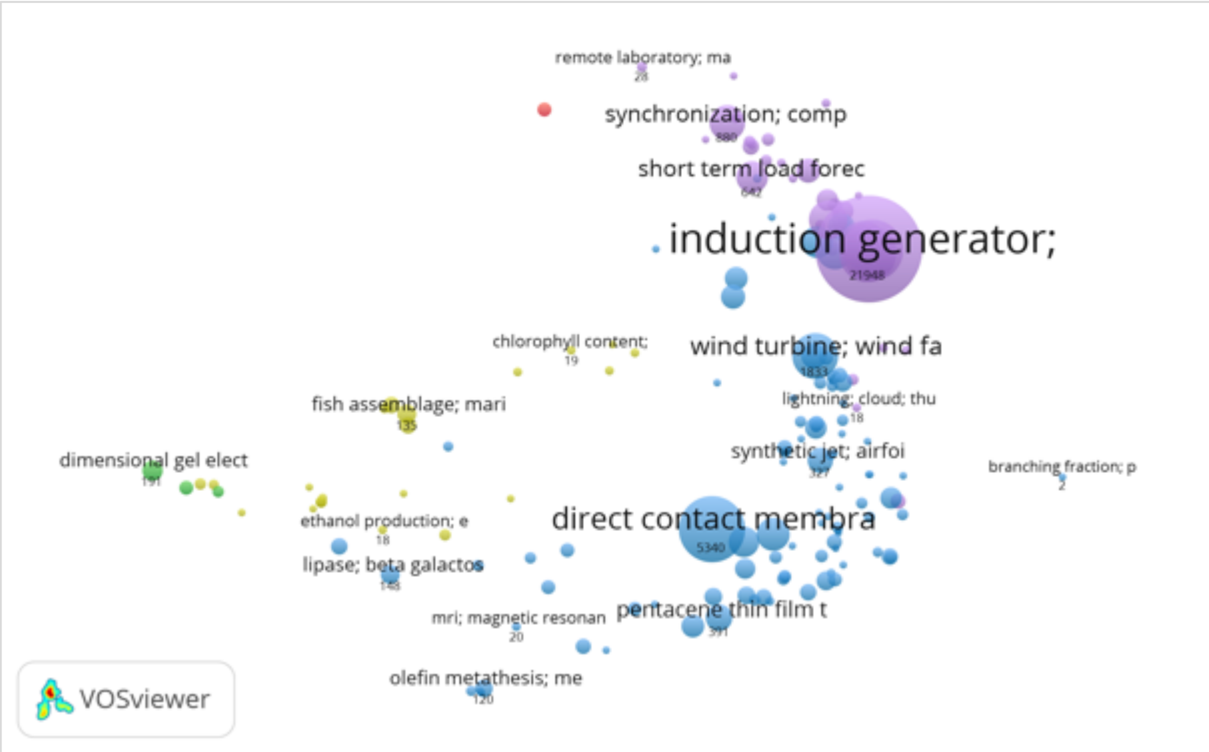


2010-2019

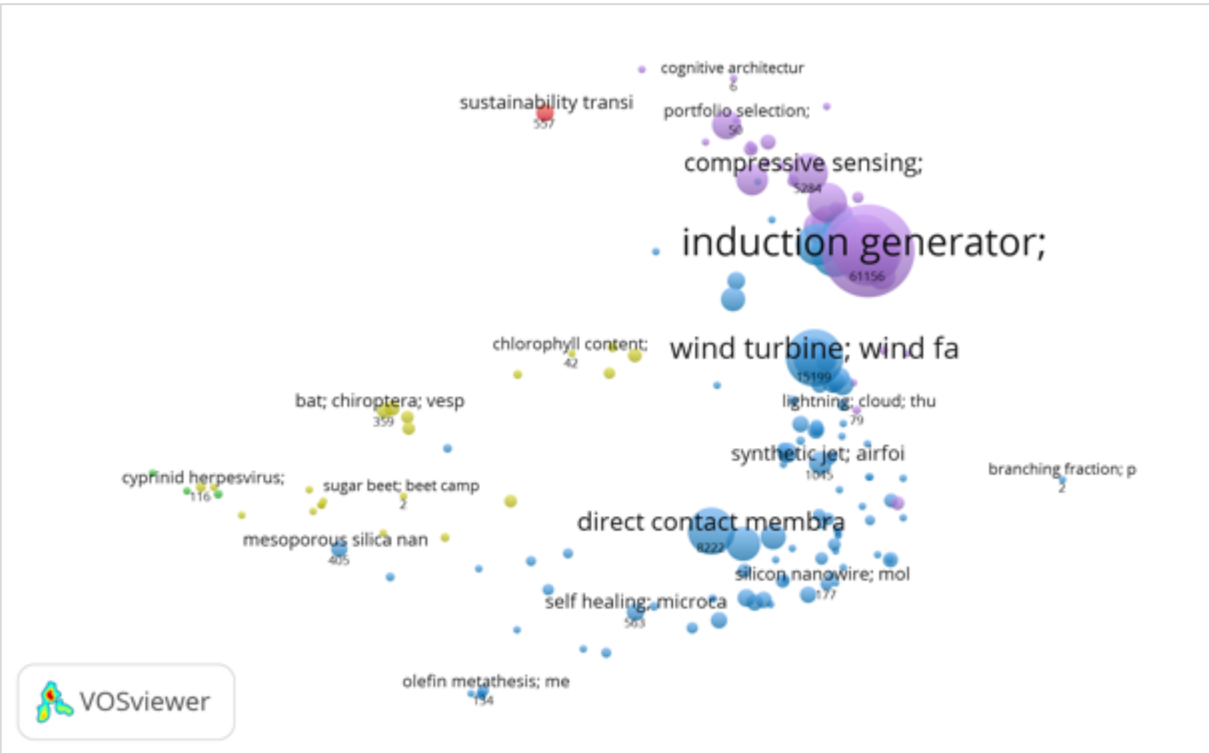


A.4 Wind power technology

2000-2009

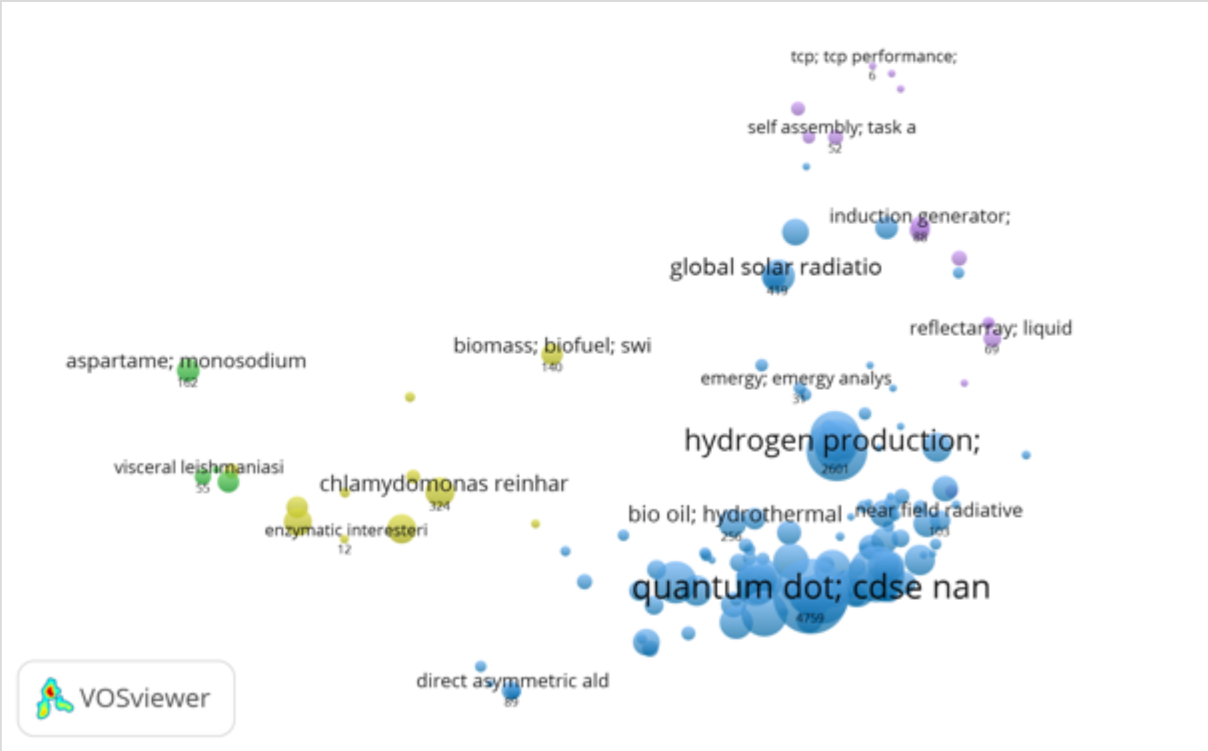


2010-2019

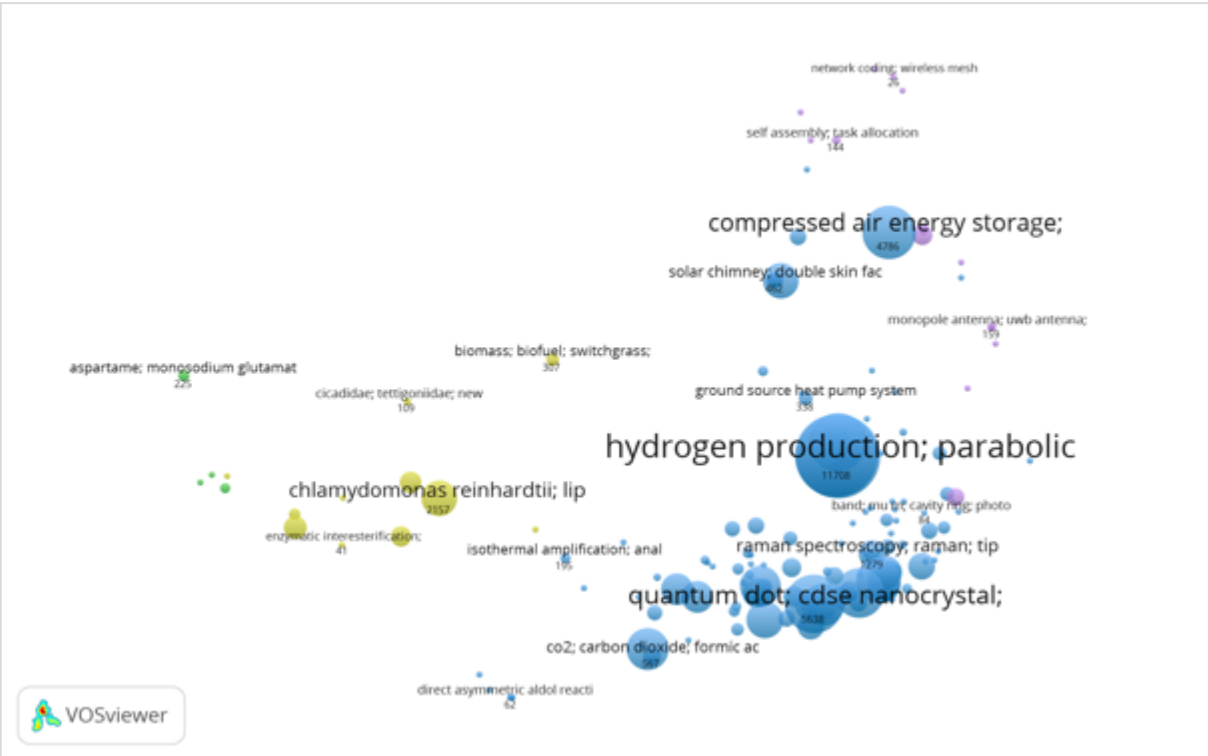


A. 5 Concentrated solar power (CSP)

2000-2009

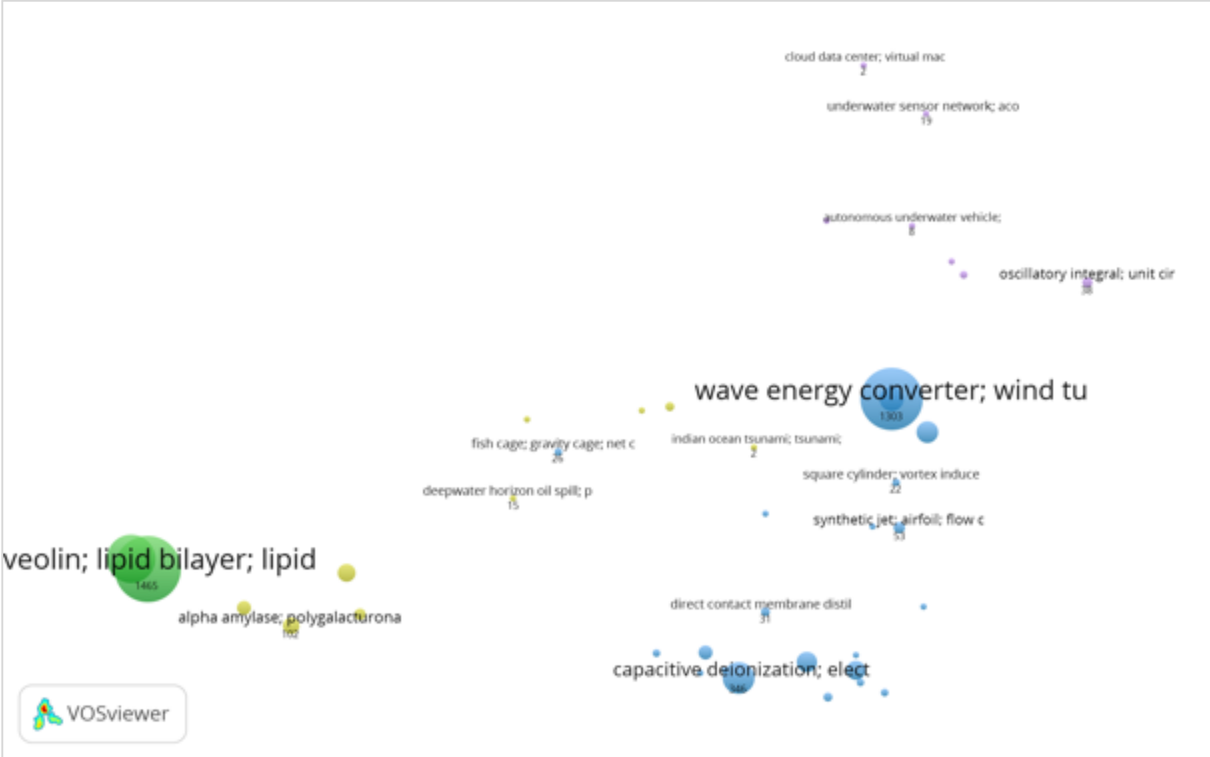


2010-2019

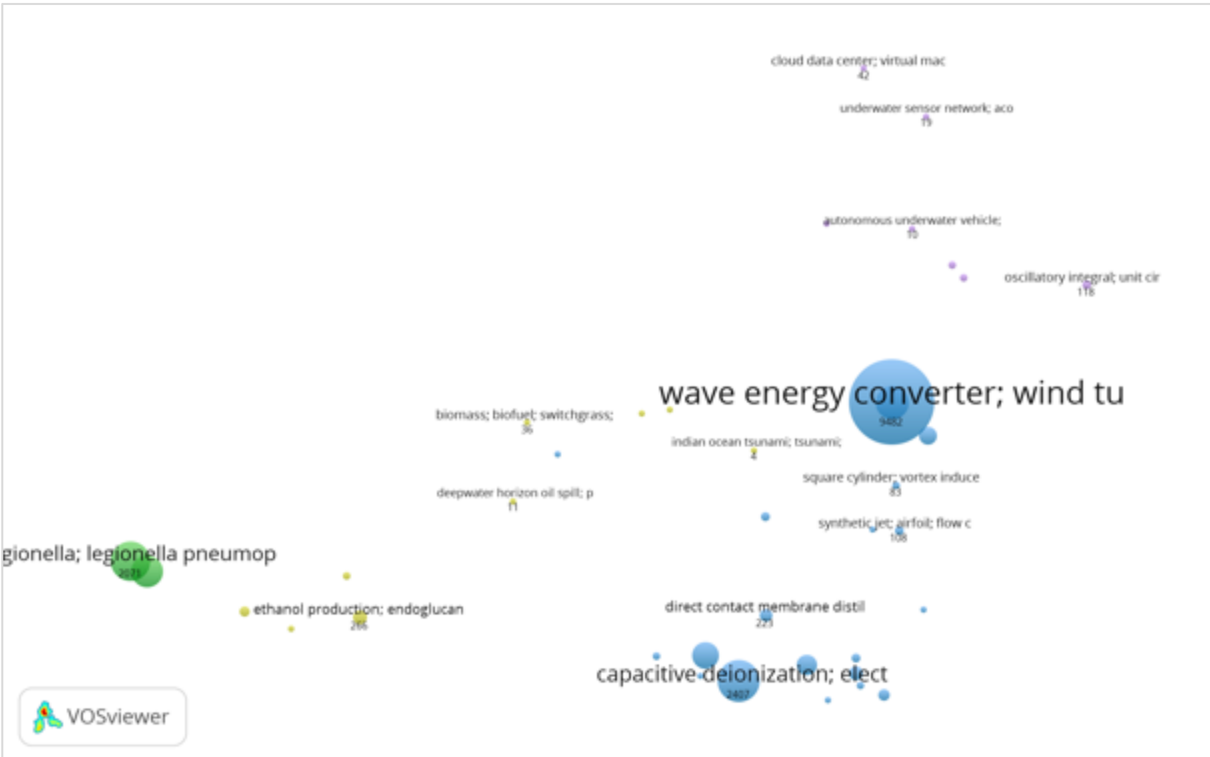


A. 6 Ocean energy

2000-2009



2010-2019



Appendix B. Skewness degree of the data

	Variable	Indicator
KNI	Knowledge complexity	KNI (scores)
RD	Scientific relatedness	Relatedness density (scores)
C	Technological and infrastructural carbon lock-in	Electricity generated from fossil fuels (GWh)
K	Knowledge accumulation	Frequency of citations in patents
CL	Access to complementary knowledge	Complementary relatedness density multiplied by the number of interregional linkages (scores)
GDP	Level of economic development	GDP per capita (euros)
P	Population	Number of inhabitants
M	Renewable energy markets	Installed capacity (MW)

Period I: 2000 – 2009

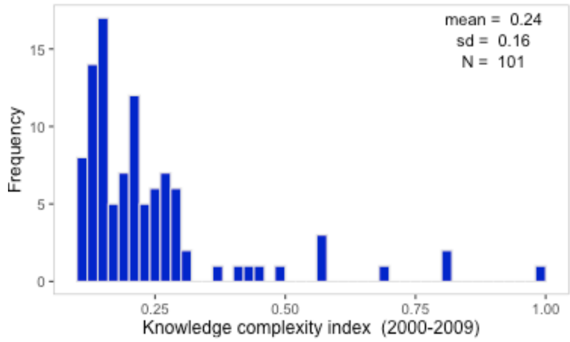
Variable	Hydropower	Geothermal	Solar PV	Wind power	CSP	Ocean energy
KNI	2,6	2,6	3	2	2,9	1,2
RD	0,9	1,3	0,9	1,2	1,2	0,9
CL	-0,5	-0,5	-0,4	-0,4	-0,4	-0,4
K	4,8	4,3	2,9	3,3	2,9	3,2
CK	2,1	1,5	1,8	2,6	2	1,9
GDP	1,9	0,6	0,4	-0,1	0,3	-0,3
P	1,9	1,7	2,4	2,3	2,3	2
M	1,5	1,8	1,2	0,5	2,7	1,9

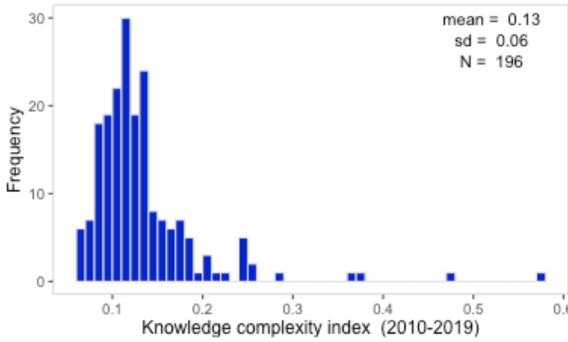
Period II: 2010– 2019

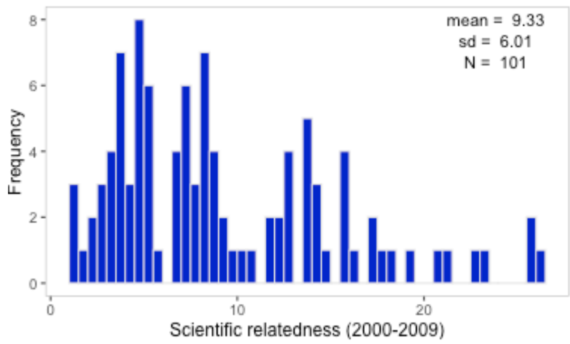
Variable	Hydropower	Geothermal	Solar PV	Wind power	CSP	Ocean energy
KNI	2	4,1	-0,6	2	0	4,1
RD	0,7	1,2	0,3	0,9	0,5	0,9
CL	-0,2	-0,1	-0,1	-0,1	-0,1	-0,2
K	5,3	3,4	2,5	4,5	3,1	2,7
CK	2,5	2,4	2	2,1	2	3,1
GDP	0,6	-0,1	0,5	0,6	0,4	0,6
P	2,3	2,1	2,5	2,5	2,5	2,4
M	1,8	9,9	0,7	0,3	2,8	2,1

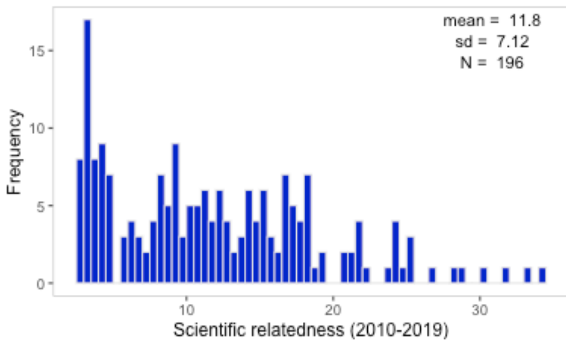
Appendix C. Distribution of the data

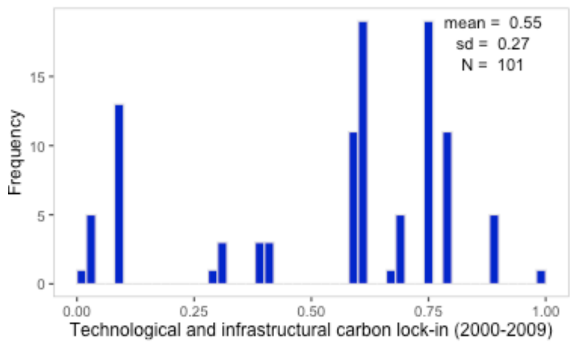
C.1 Hydropower technology (2000-2009; 2010-2019)

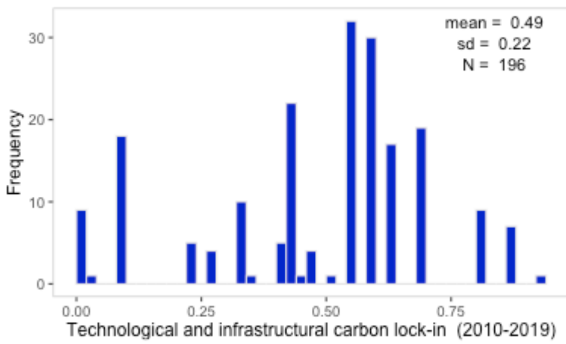


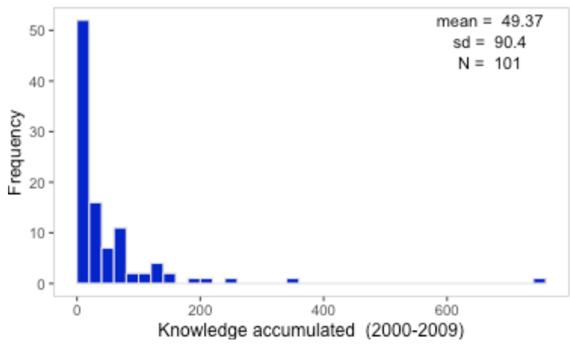


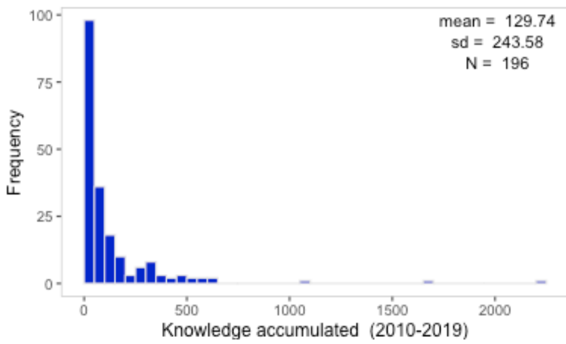


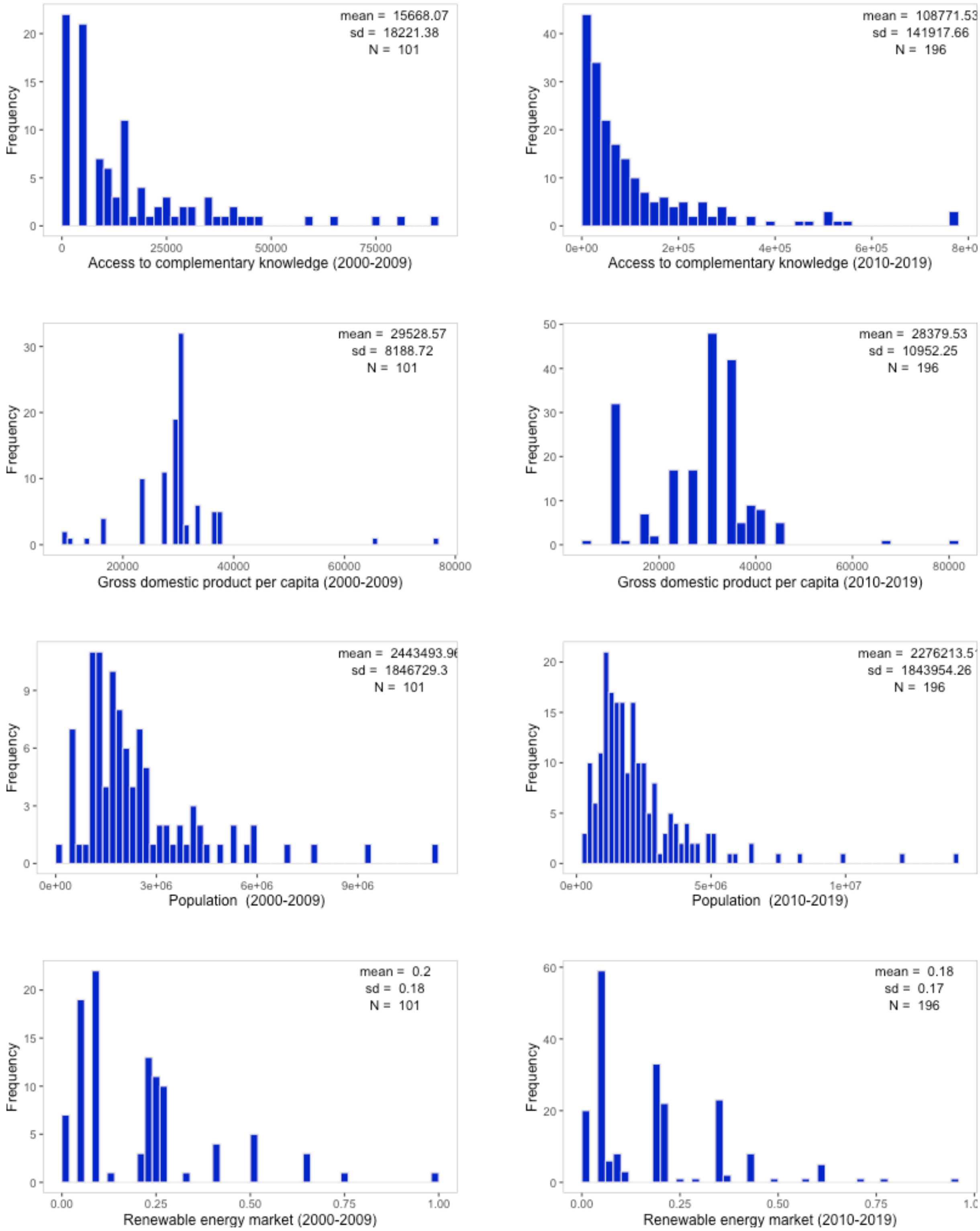




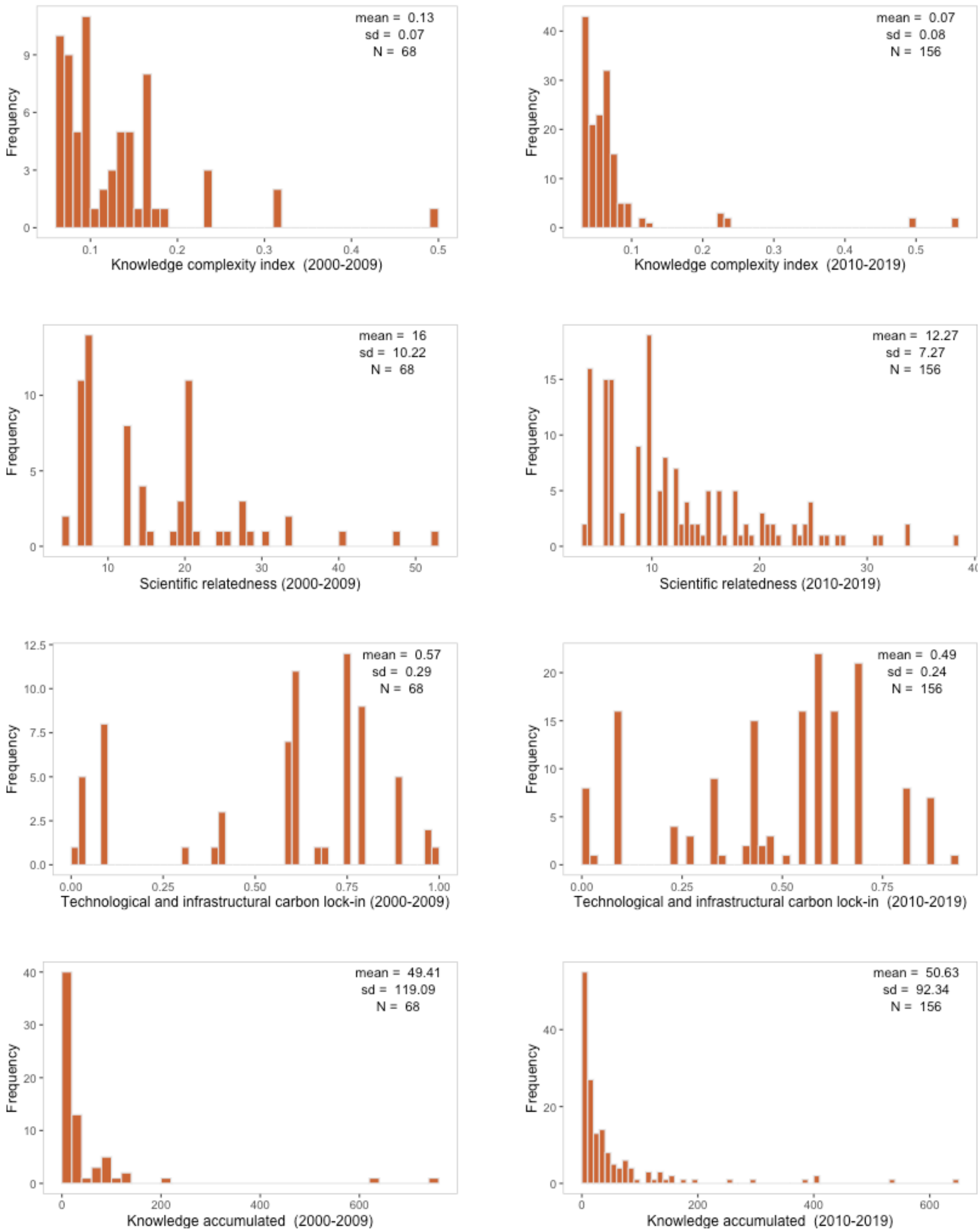


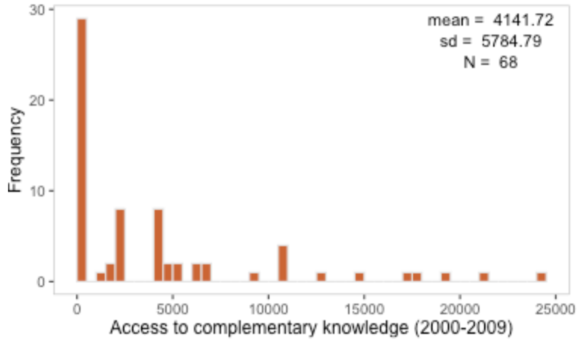


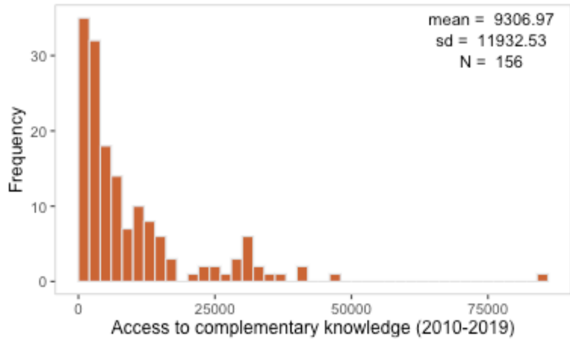



mean = 15668.07
sd = 18221.38
N = 101
Frequency
Access to complementary knowledge (2000-2009)
mean = 108771.53
sd = 141917.66
N = 196
Frequency
Access to complementary knowledge (2010-2019)
mean = 29528.57
sd = 8188.72
N = 101
Frequency
Gross domestic product per capita (2000-2009)
mean = 28379.53
sd = 10952.25
N = 196
Frequency
Gross domestic product per capita (2010-2019)
mean = 2443493.9
sd = 1846729.3
N = 101
Frequency
Population (2000-2009)
mean = 2276213.5
sd = 1843954.26
N = 196
Frequency
Population (2010-2019)
mean = 0.2
sd = 0.18
N = 101
Frequency
Renewable energy market (2000-2009)
mean = 0.18
sd = 0.17
N = 196
Frequency
Renewable energy market (2010-2019)

C.2 Geothermal energy technology (2000-2009; 2010-2019)




Frequency
mean = 4141.72
sd = 5784.79
N = 68
Access to complementary knowledge (2000-2009)


Frequency
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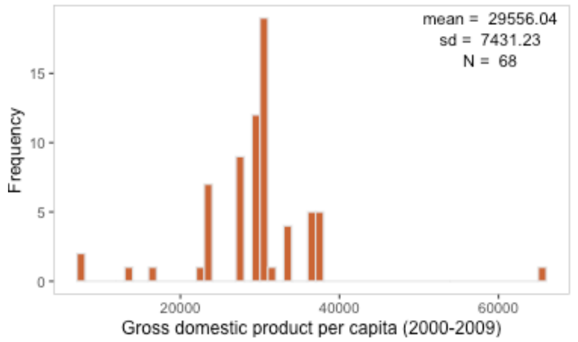
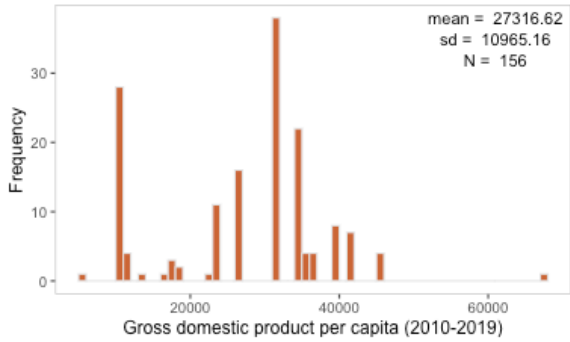
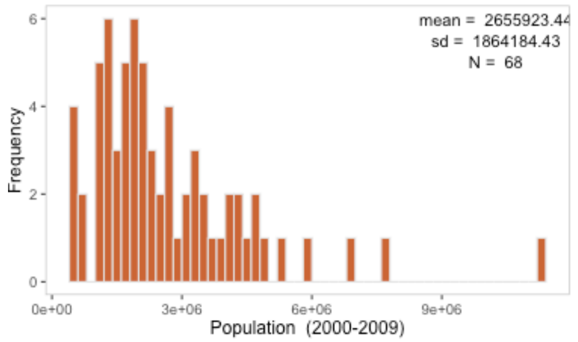
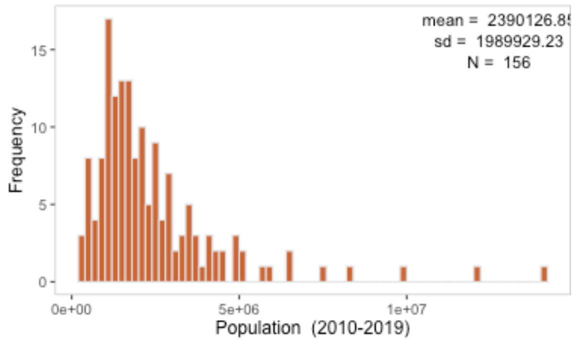
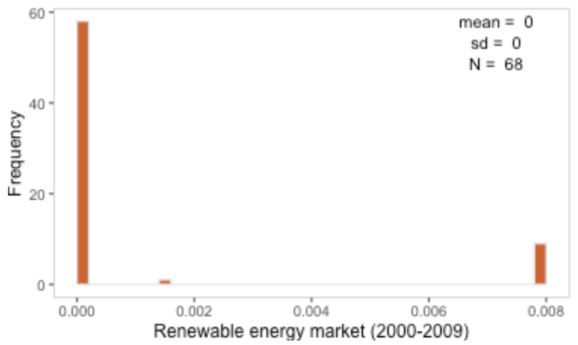
sd = 11932.53
N = 156
Access to complementary knowledge (2010-2019)

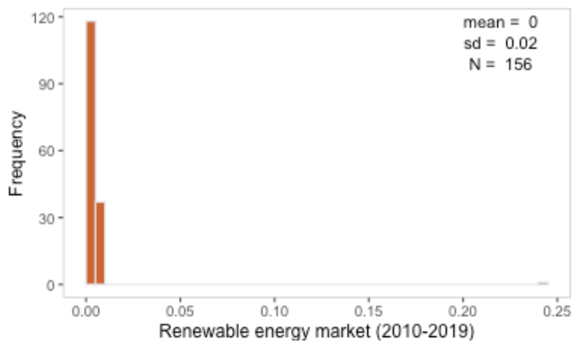

Frequency
mean = 29556.04
sd = 7431.23
N = 68
Gross domestic product per capita (2000-2009)


Frequency
mean = 27316.62
sd = 10965.16
N = 156
Gross domestic product per capita (2010-2019)


Frequency
mean = 2655923.4
sd = 1864184.43
N = 68
Population (2000-2009)


Frequency
mean = 2390126.8
sd = 1989929.23
N = 156
Population (2010-2019)


Frequency
mean = 0
sd = 0
N = 68
Renewable energy market (2000-2009)


Frequency
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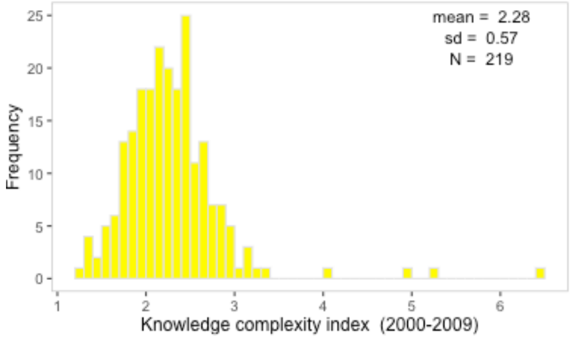
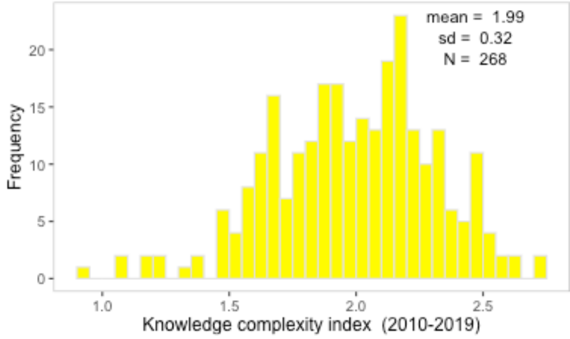
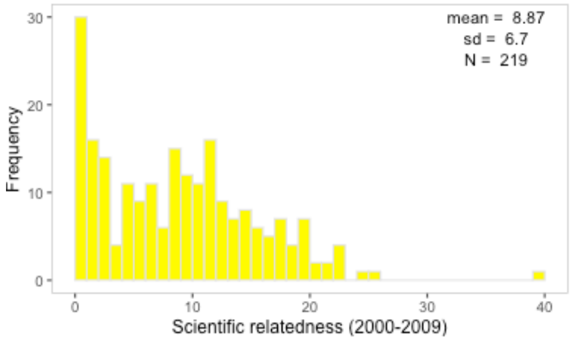
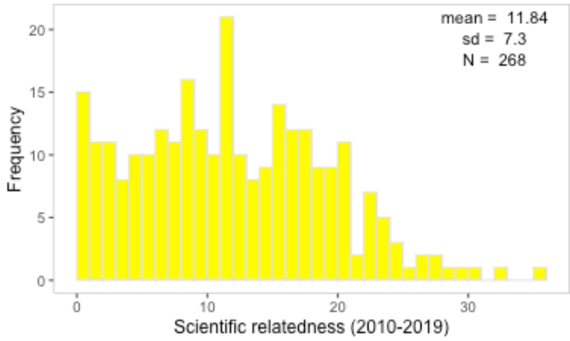
N = 156
Renewable energy market (2010-2019)

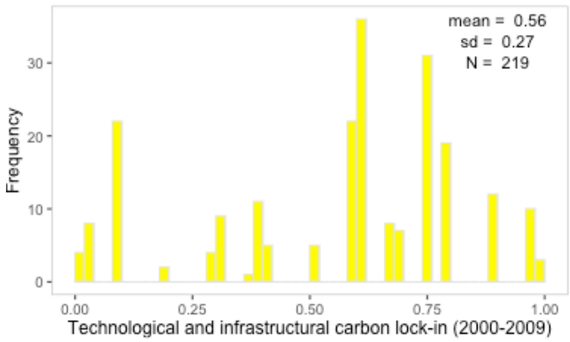
C.3 Solar PV technology (2000-2009; 2010-2019)

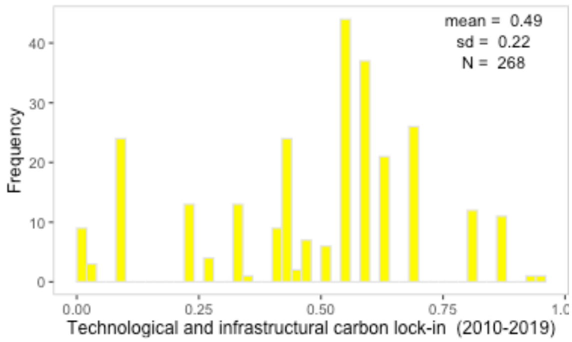


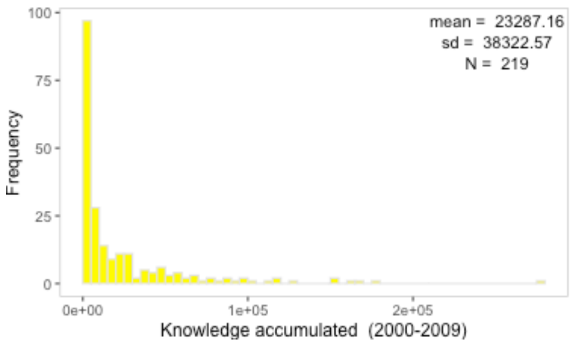


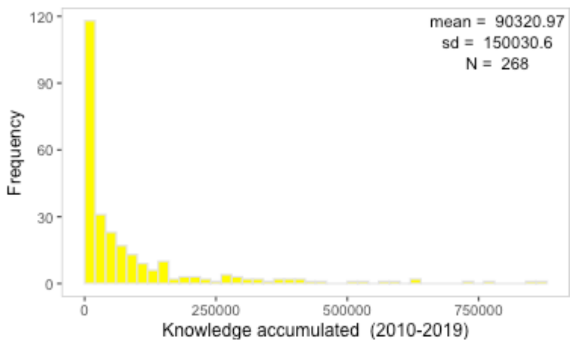


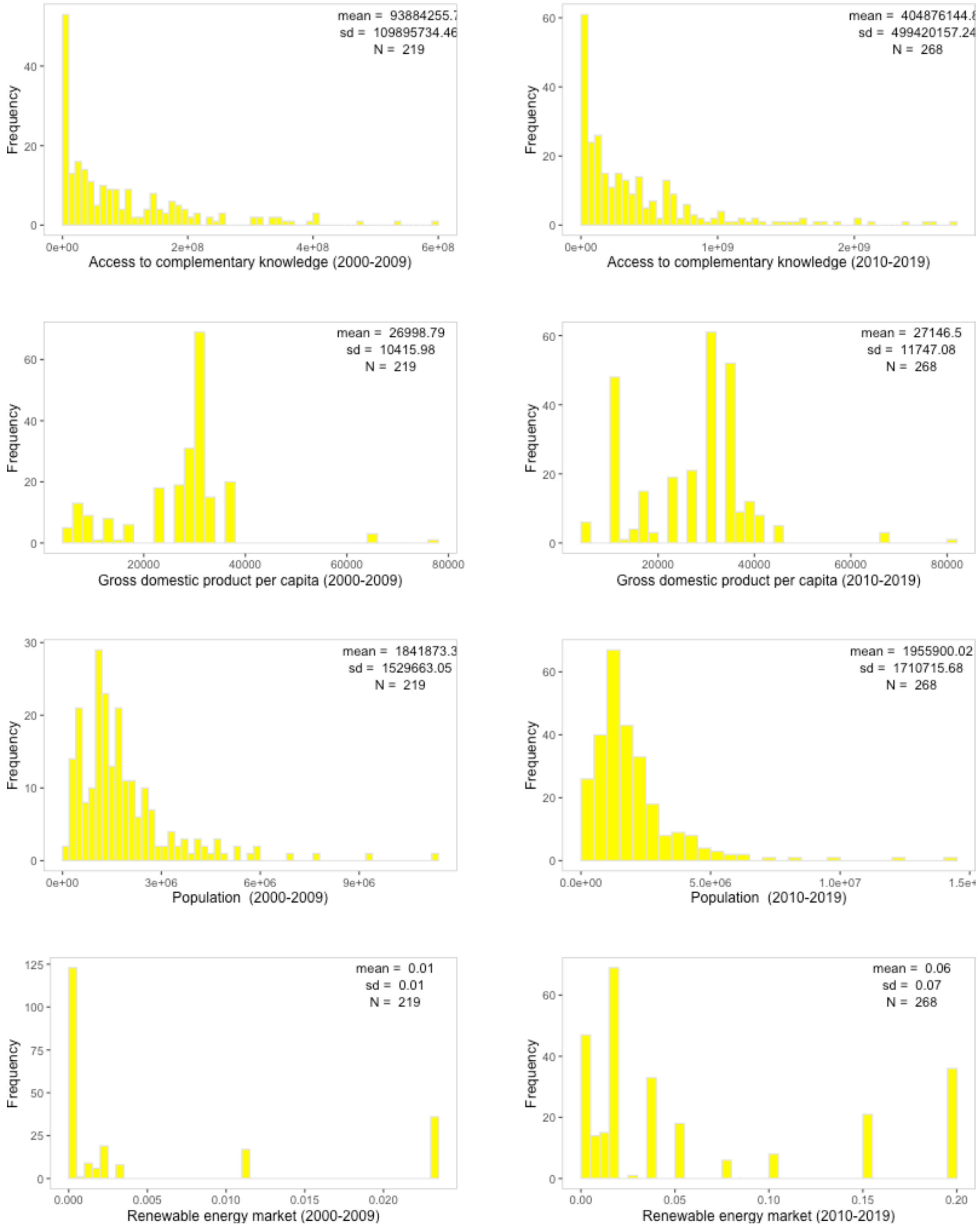




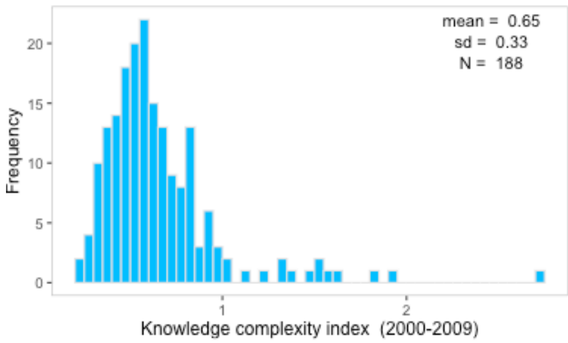


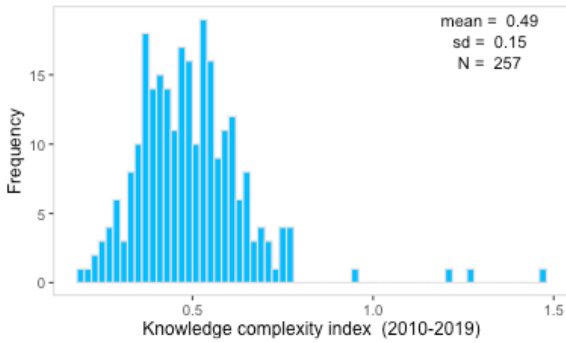


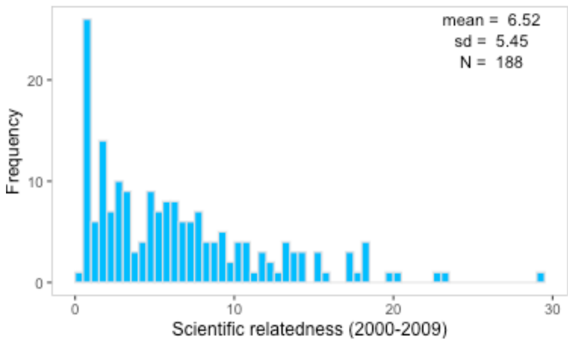


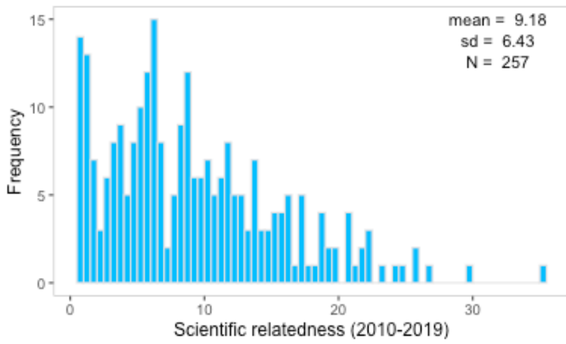

mean = 93884255.7
sd = 109895734.46
N = 219
Frequency
Access to complementary knowledge (2000-2009)
mean = 404876144.8
sd = 499420157.24
N = 268
Frequency
Access to complementary knowledge (2010-2019)
mean = 26998.79
sd = 10415.98
N = 219
Frequency
Gross domestic product per capita (2000-2009)
mean = 27146.5
sd = 11747.08
N = 268
Frequency
Gross domestic product per capita (2010-2019)
mean = 1841873.3
sd = 1529663.05
N = 219
Frequency
Population (2000-2009)
mean = 1955900.02
sd = 1710715.68
N = 268
Frequency
Population (2010-2019)
mean = 0.01
sd = 0.01
N = 219
Frequency
Renewable energy market (2000-2009)
mean = 0.06
sd = 0.07
N = 268
Frequency
Renewable energy market (2010-2019)

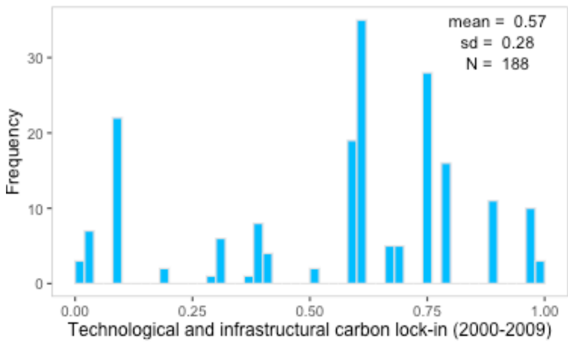
C.4 Wind power technology (2000-2009; 2010-2019)

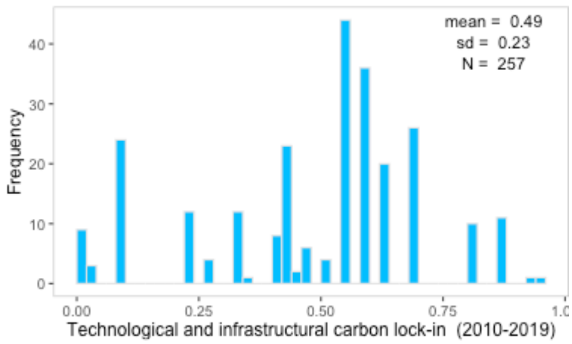


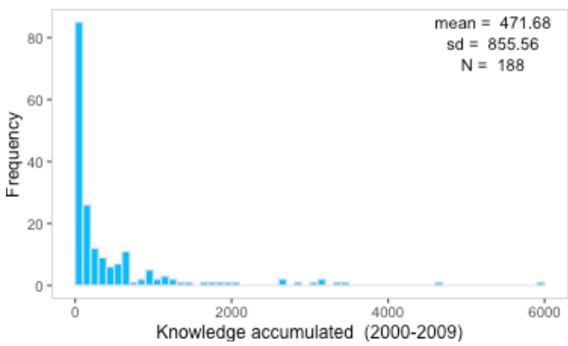


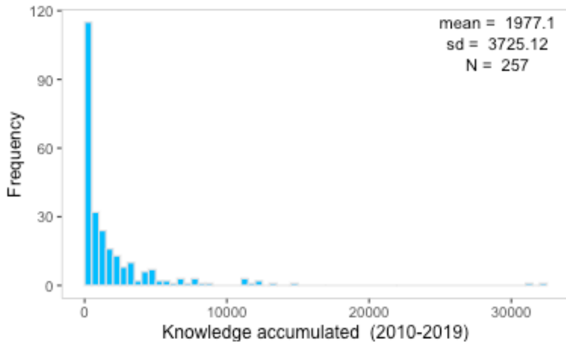


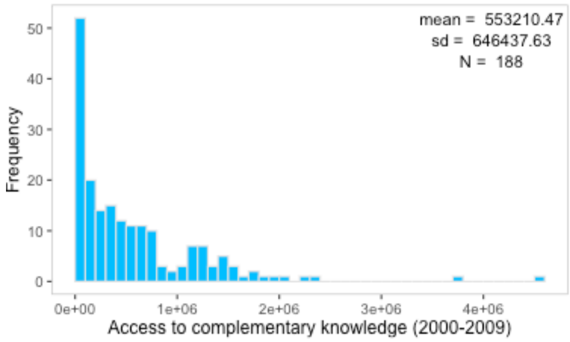


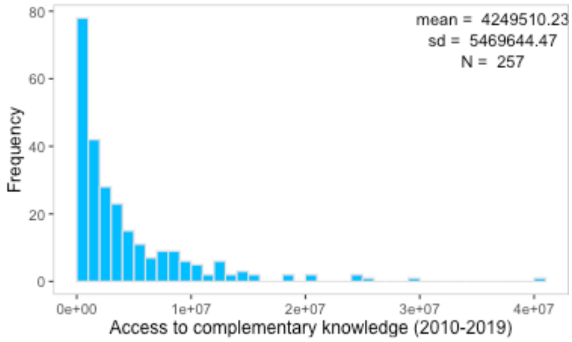


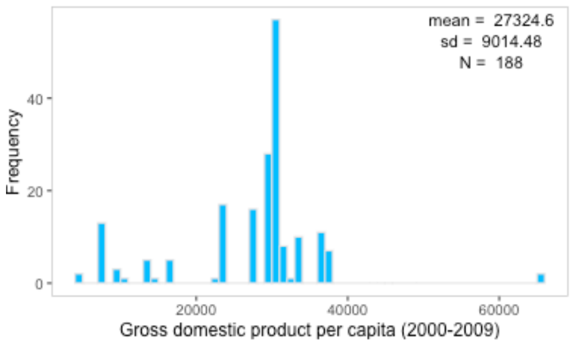


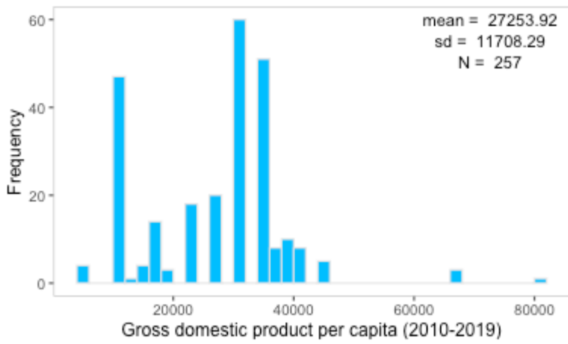


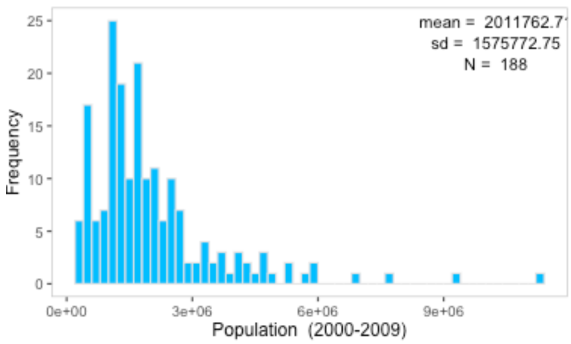


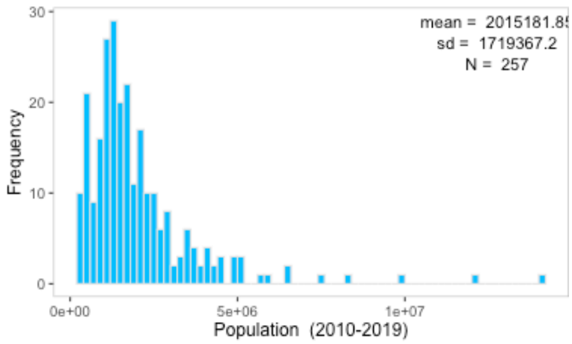

mean = 553210.47
sd = 646437.63
N = 188
Frequency
0
10
20
30
40
50
0e+00
1e+06
2e+06
3e+06
4e+06
Access to complementary knowledge (2000-2009)

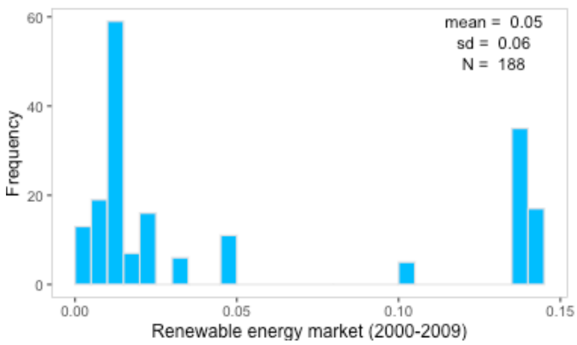

mean = 4249510.23
sd = 5469644.47
N = 257
Frequency
0
20
40
60
80
0e+00
1e+07
2e+07
3e+07
4e+07
Access to complementary knowledge (2010-2019)

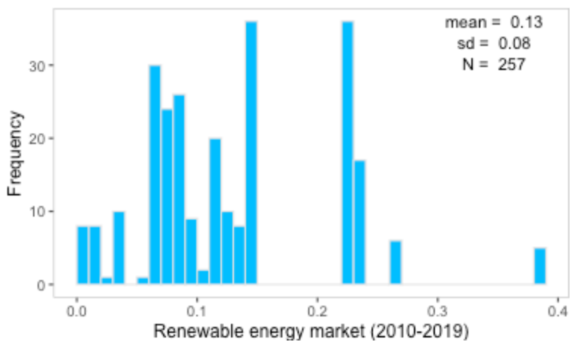

mean = 27324.6
sd = 9014.48
N = 188
Frequency
0
20
40
20000
40000
60000
Gross domestic product per capita (2000-2009)


mean = 27253.92
sd = 11708.29
N = 257
Frequency
0
20
40
60
20000
40000
60000
80000
Gross domestic product per capita (2010-2019)

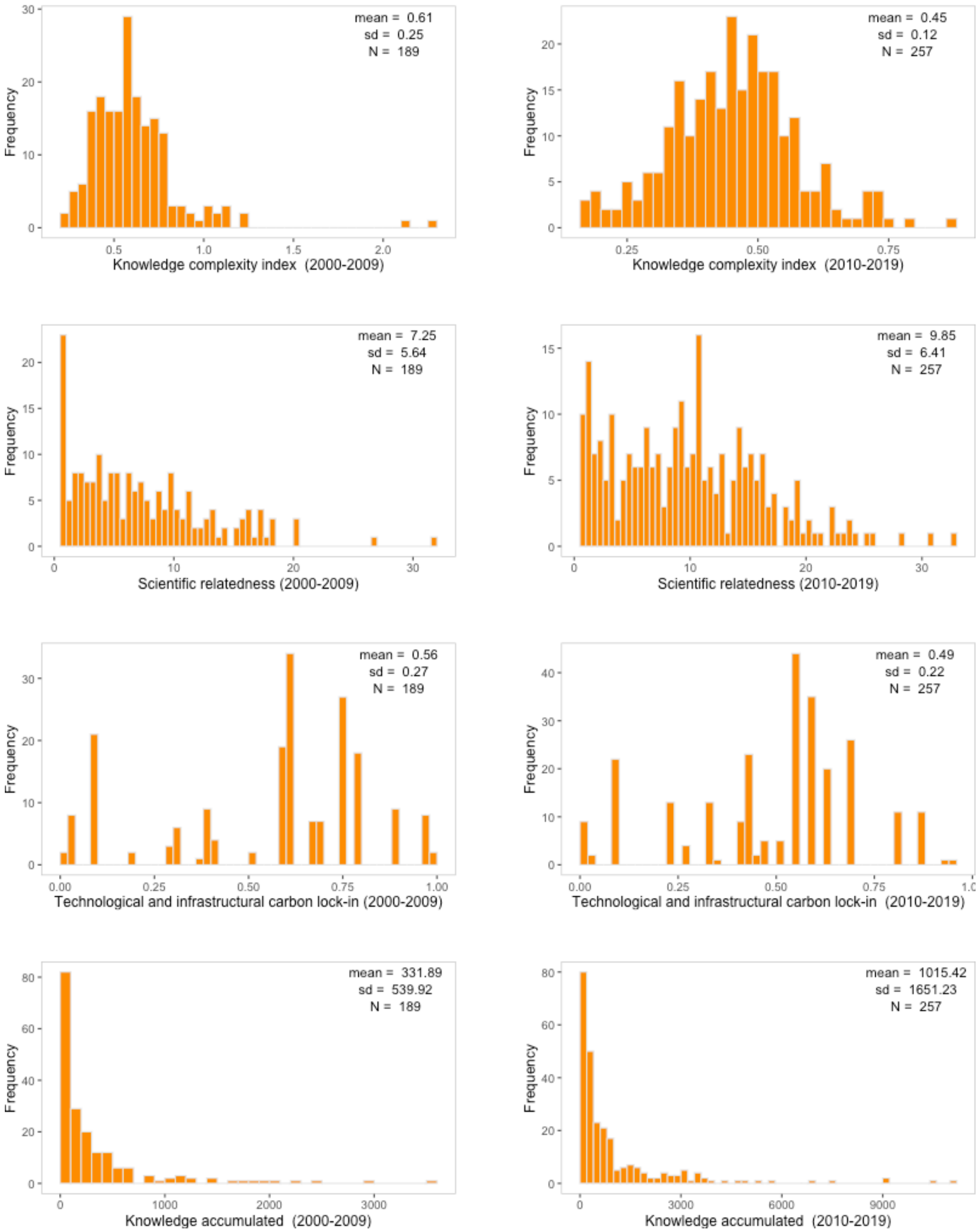

mean = 2011762.7
sd = 1575772.75
N = 188
Frequency
0
5
10
15
20
25
0e+00
3e+06
6e+06
9e+06
Population (2000-2009)

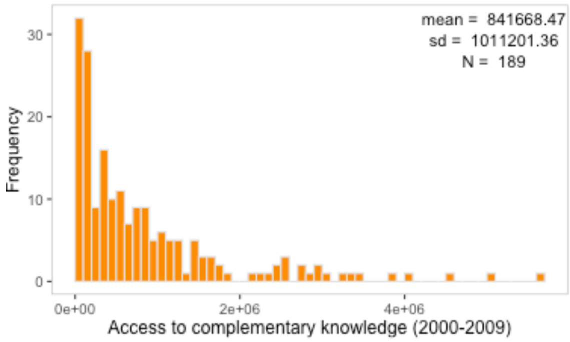

mean = 2015181.8
sd = 1719367.2
N = 257
Frequency
0
10
20
30
0e+00
5e+06
1e+07
Population (2010-2019)

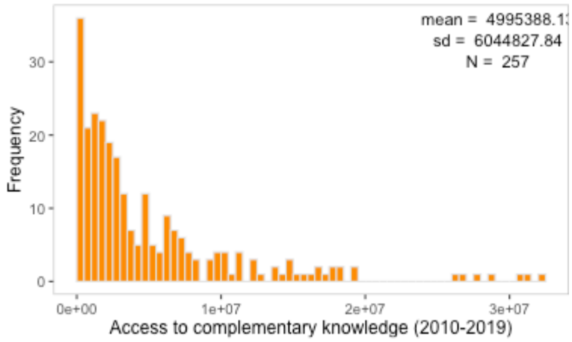

mean = 0.05
sd = 0.06
N = 188
Frequency
0
20
40
60
0.00
0.05
0.10
0.15
Renewable energy market (2000-2009)

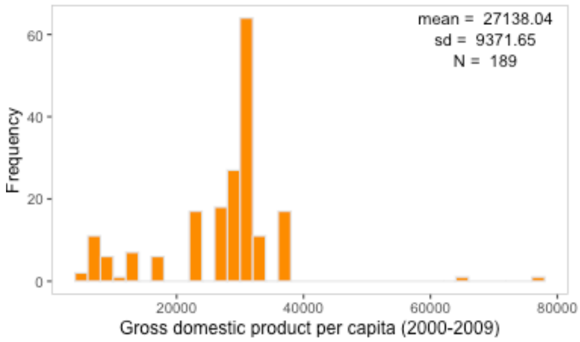

mean = 0.13
sd = 0.08
N = 257
Frequency
0
10
20
30
0.0
0.1
0.2
0.3
0.4
Renewable energy market (2010-2019)

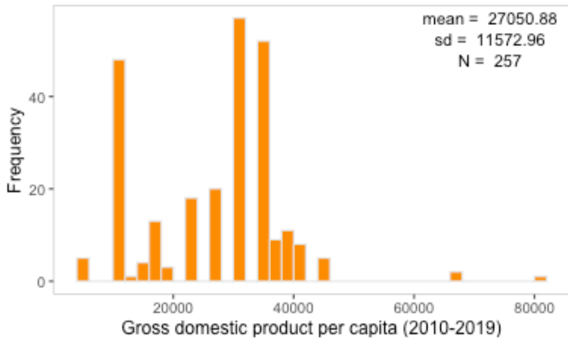
C.5 Concentrated solar power (CSP) technology (2000-2009; 2010-2019)

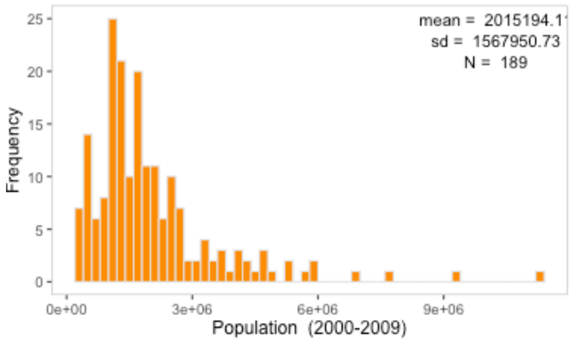


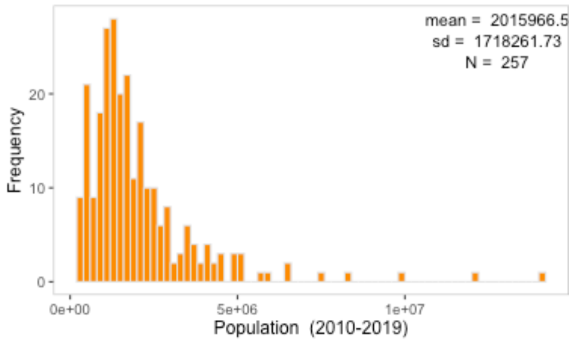

mean = 841668.47
sd = 1011201.36
N = 189
Frequency
0
10
20
30
0e+00
2e+06
4e+06
Access to complementary knowledge (2000-2009)

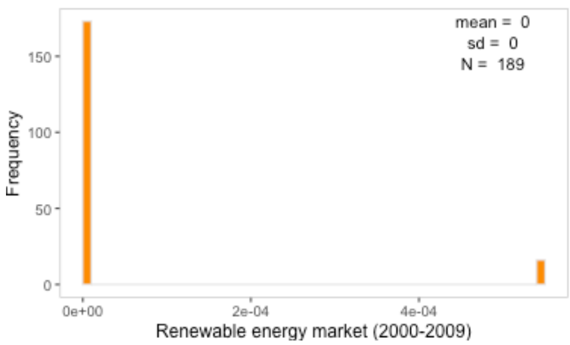

mean = 4995388.1
sd = 6044827.84
N = 257
Frequency
0
10
20
30
0e+00
1e+07
2e+07
3e+07
Access to complementary knowledge (2010-2019)

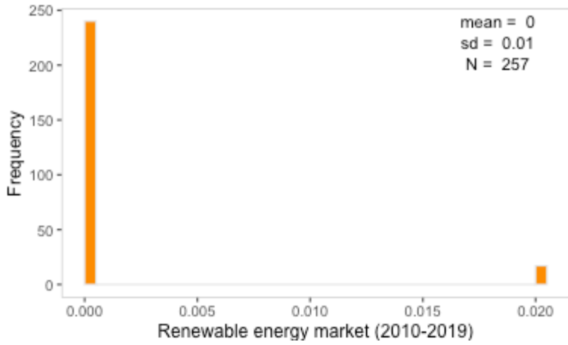

mean = 27138.04
sd = 9371.65
N = 189
Frequency
0
20
40
60
20000
40000
60000
80000
Gross domestic product per capita (2000-2009)


mean = 27050.88
sd = 11572.96
N = 257
Frequency
0
20
40
20000
40000
60000
80000
Gross domestic product per capita (2010-2019)

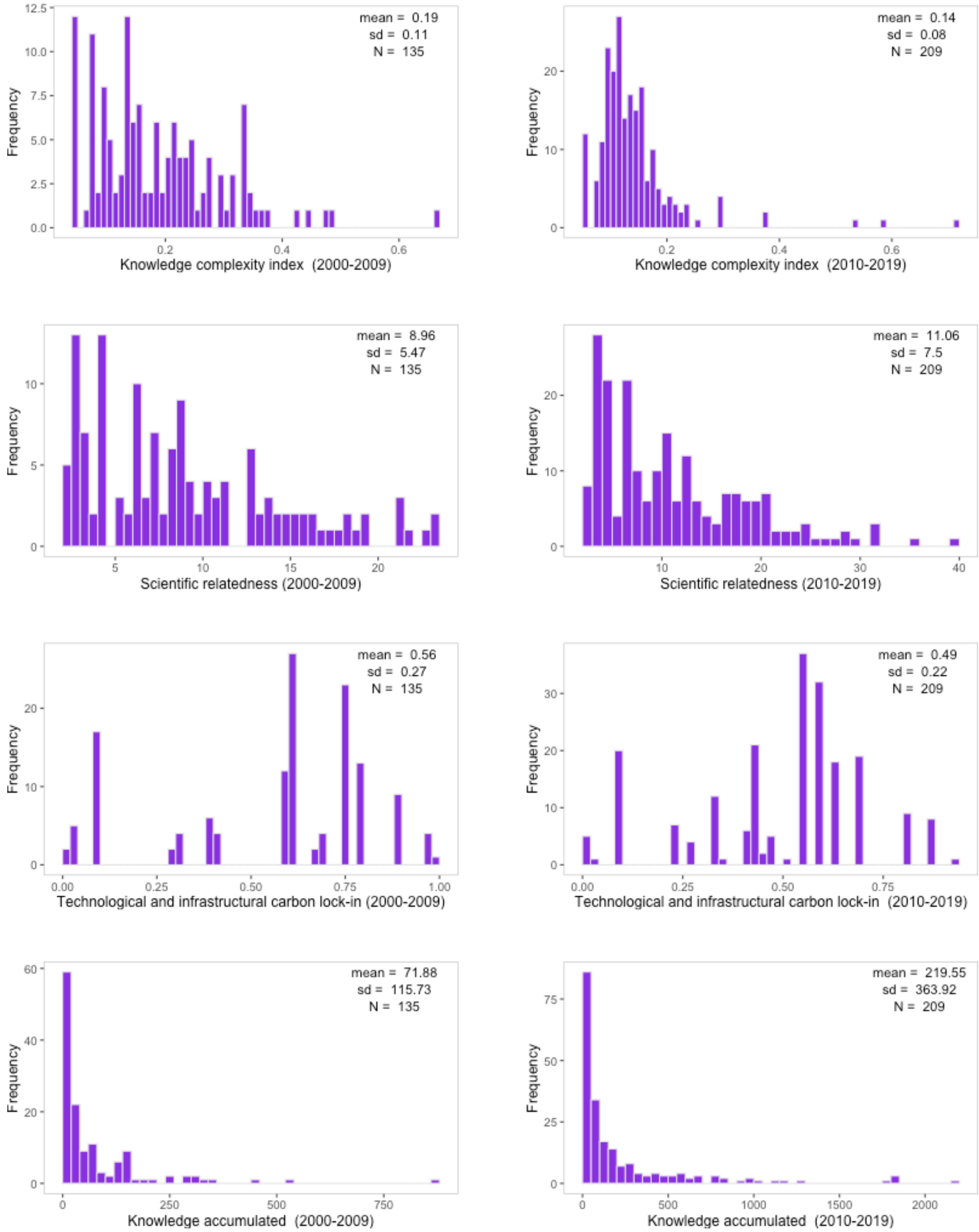

mean = 2015194.1
sd = 1567950.73
N = 189
Frequency
0
5
10
15
20
25
0e+00
3e+06
6e+06
9e+06
Population (2000-2009)

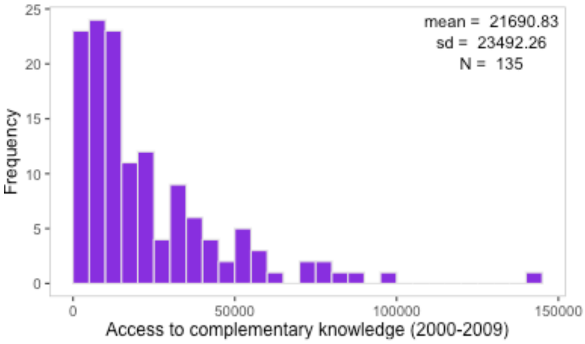

mean = 2015966.5
sd = 1718261.73
N = 257
Frequency
0
10
20
0e+00
5e+06
1e+07
Population (2010-2019)

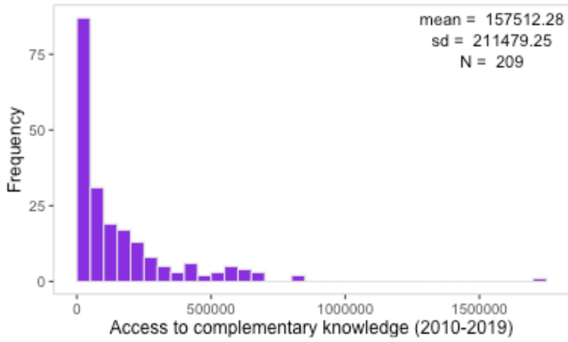

mean = 0
sd = 0
N = 189
Frequency
0
50
100
150
0e+00
2e-04
4e-04
Renewable energy market (2000-2009)

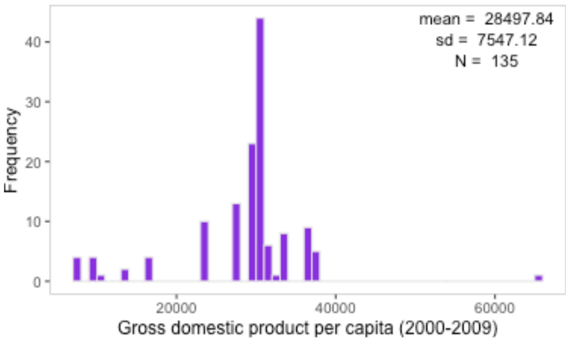

mean = 0
sd = 0.01
N = 257
Frequency
0
50
100
150
200
250
0.000
0.005
0.010
0.015
0.020
Renewable energy market (2010-2019)

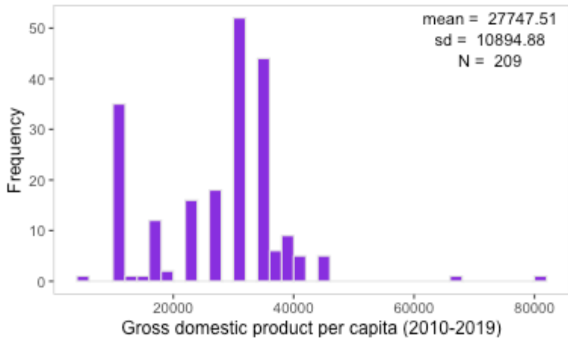
C.6 Ocean energy technology (2000-2009; 2010-2019)

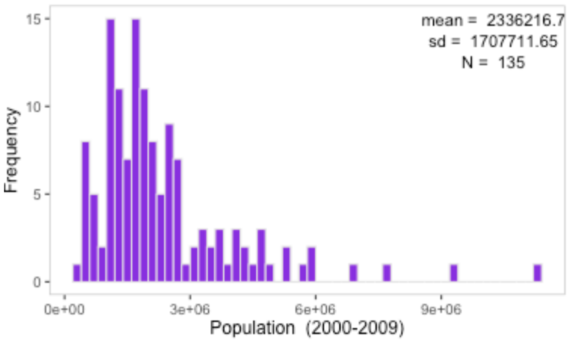


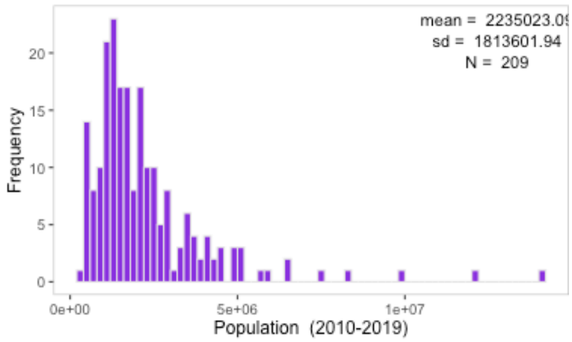

mean = 21690.83
sd = 23492.26
N = 135
Frequency
Access to complementary knowledge (2000-2009)

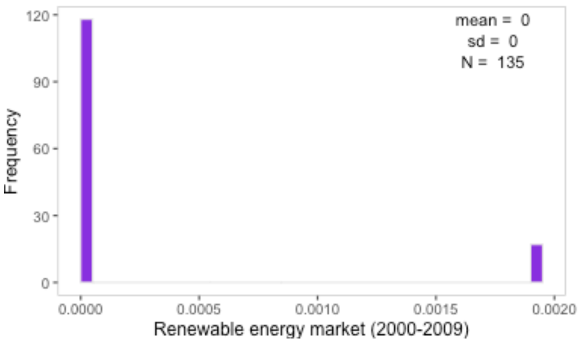

mean = 157512.28
sd = 211479.25
N = 209
Frequency
Access to complementary knowledge (2010-2019)

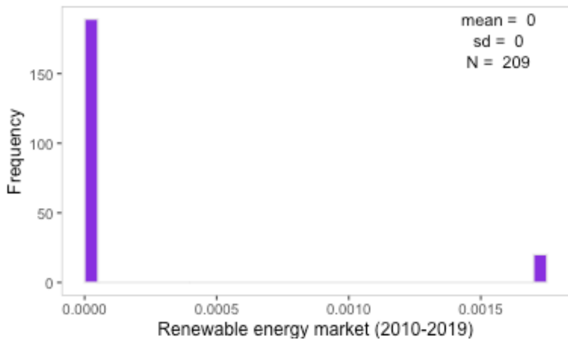

mean = 28497.84
sd = 7547.12
N = 135
Frequency
Gross domestic product per capita (2000-2009)


mean = 27747.51
sd = 10894.88
N = 209
Frequency
Gross domestic product per capita (2010-2019)


mean = 2336216.7
sd = 1707711.65
N = 135
Frequency
Population (2000-2009)

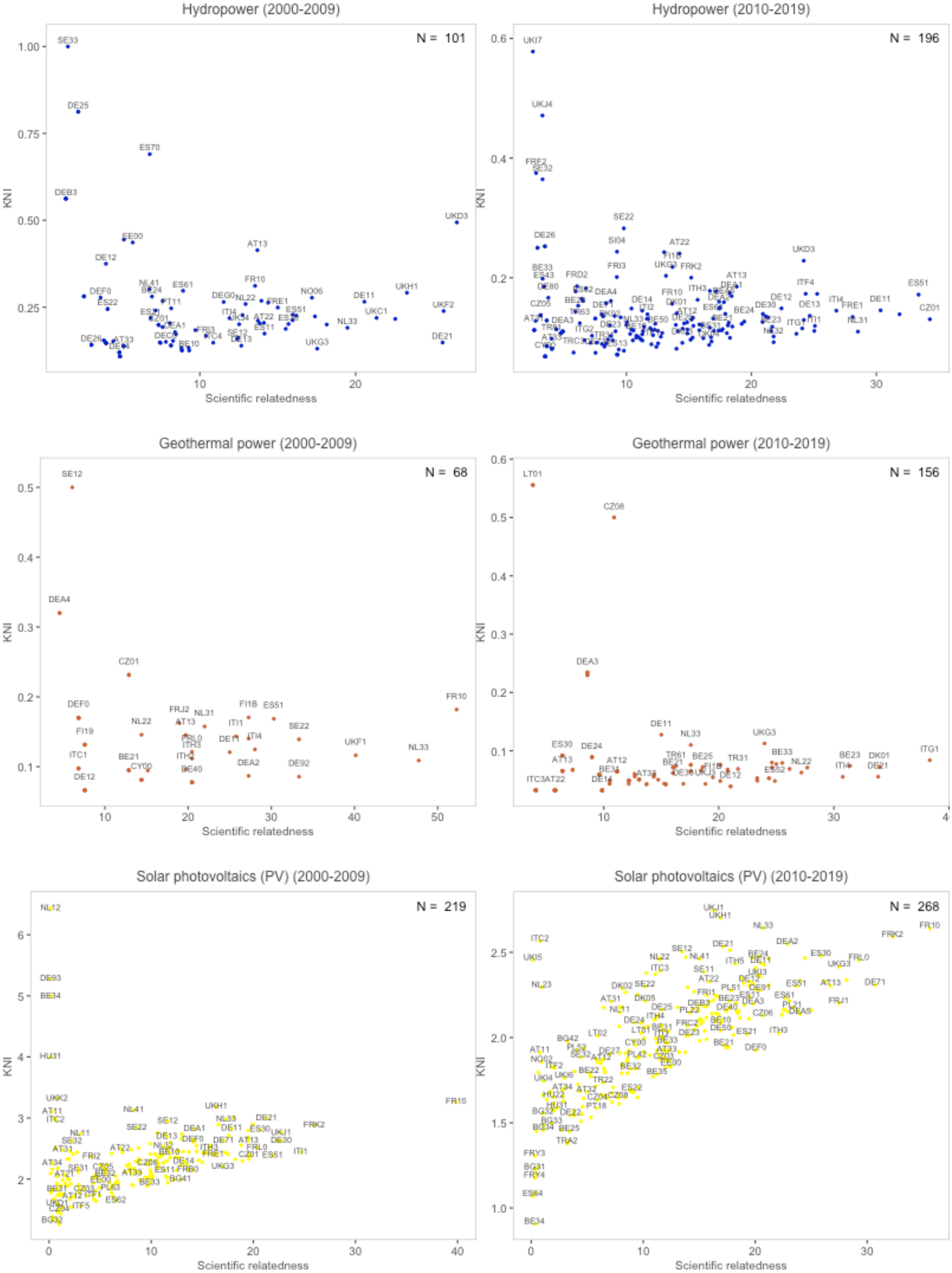

sd = 1813601.94
N = 209
Frequency
Population (2010-2019)

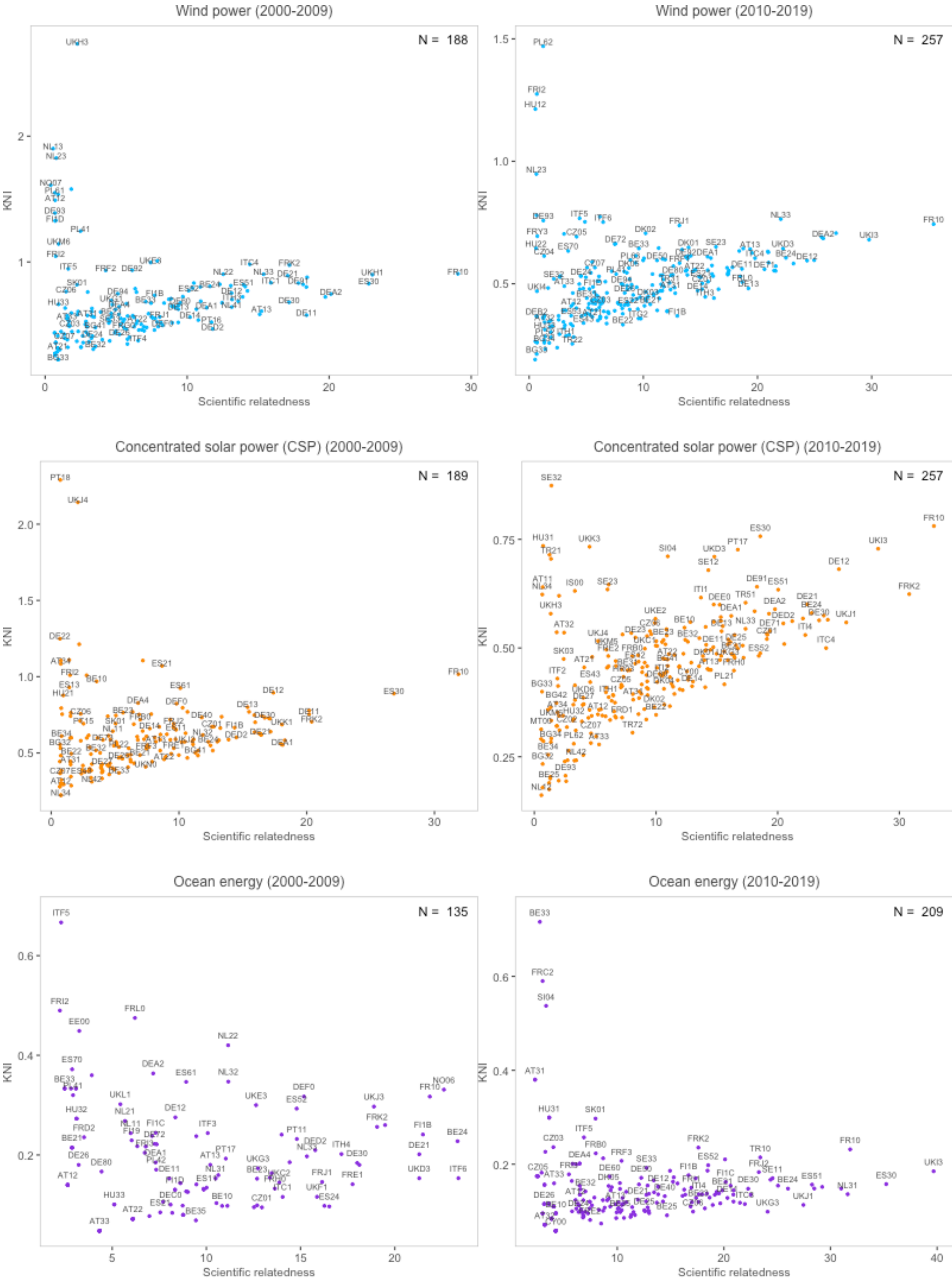

mean = 0
sd = 0
N = 135
Frequency
Renewable energy market (2000-2009)


mean = 0
sd = 0
N = 209
Frequency
Renewable energy market (2010-2019)

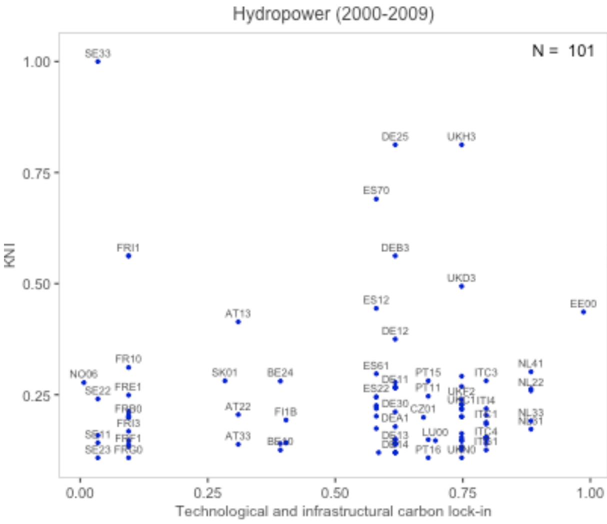
Appendix D. Scatter plots

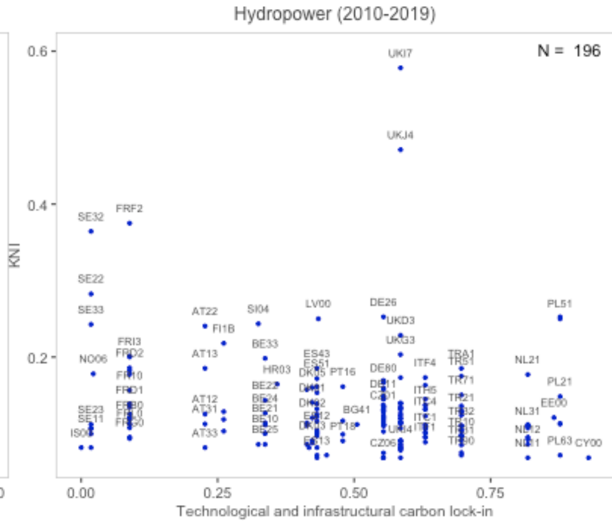
D.1 KNI and scientific relatedness (2000-2009; 2010-2019)

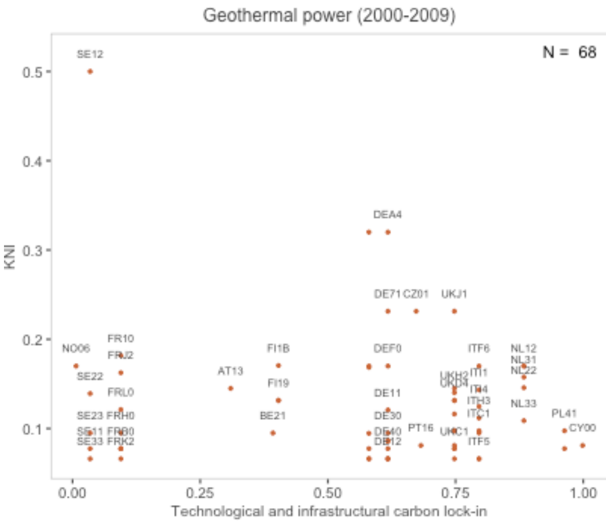


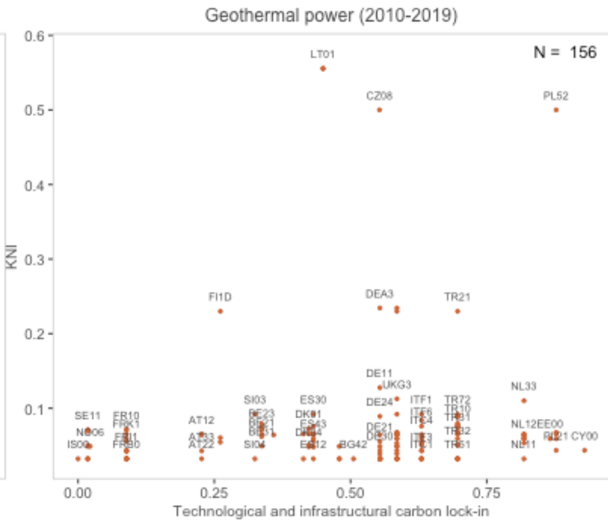

Wind power (2000-2009)
N = 188
Wind power (2010-2019)
N = 257
Concentrated solar power (CSP) (2000-2009)
N = 189
Concentrated solar power (CSP) (2010-2019)
N = 257
Ocean energy (2000-2009)
N = 135
Ocean energy (2010-2019)
N = 209
KNI
Scientific relatedness

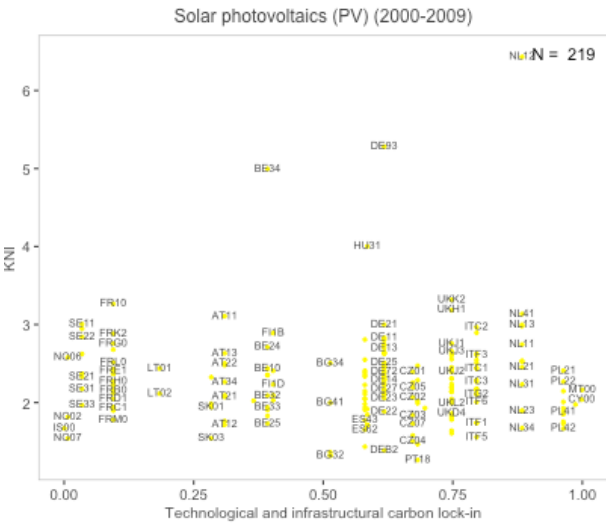
D.2 KNI and technological and infrastructural carbon lock-in (2000-2009; 2010-2019)

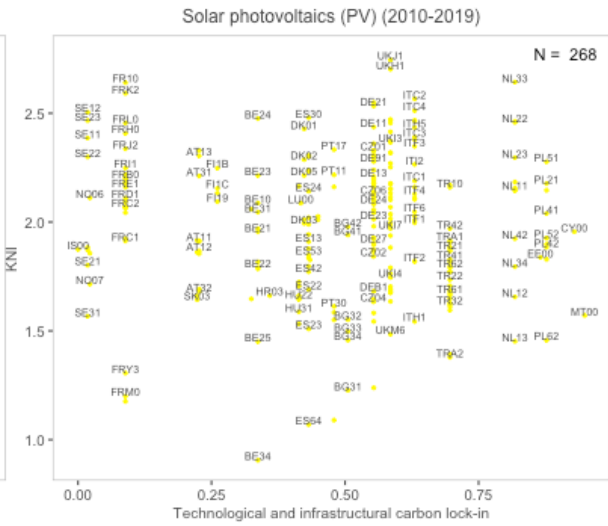


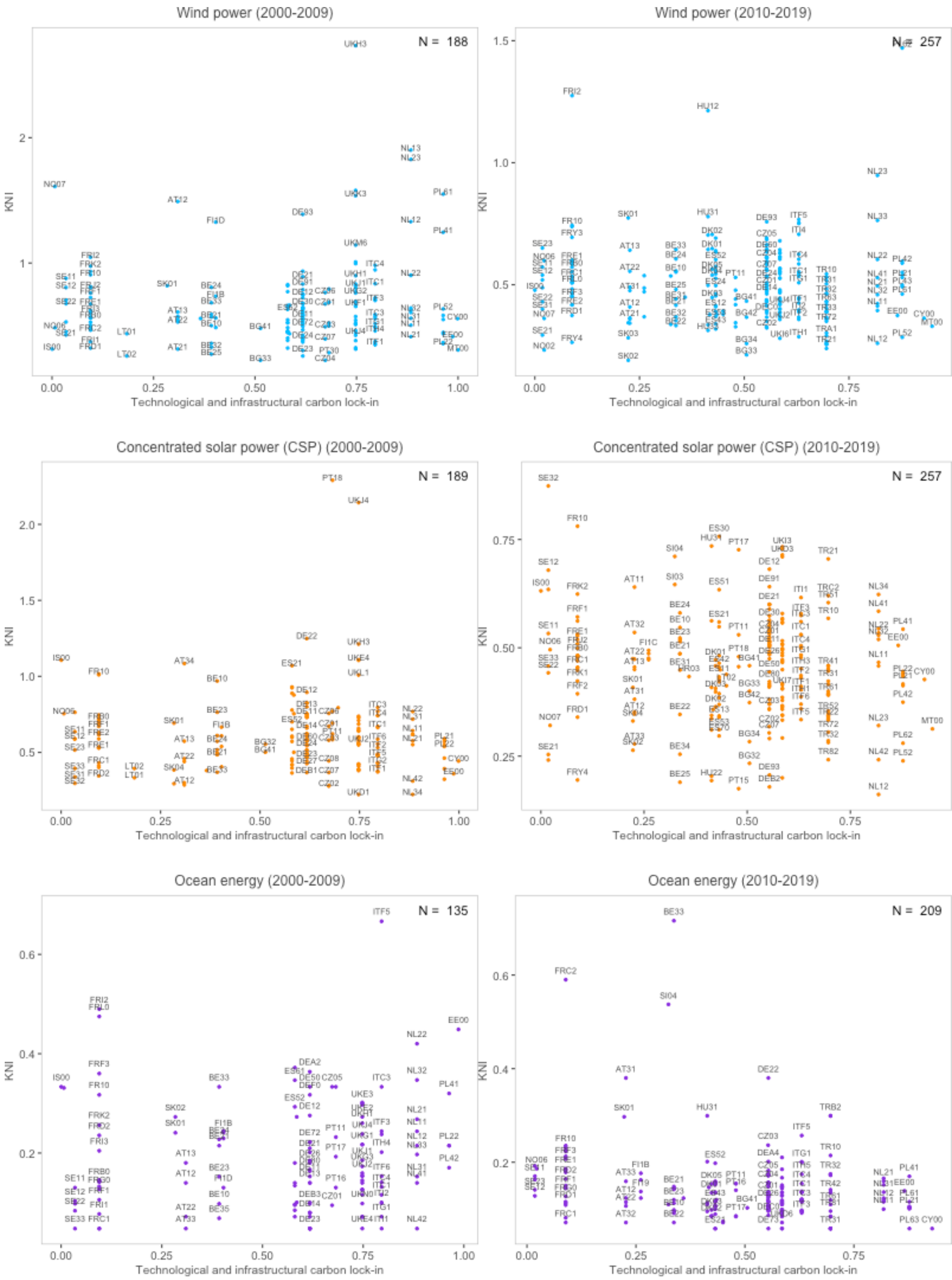




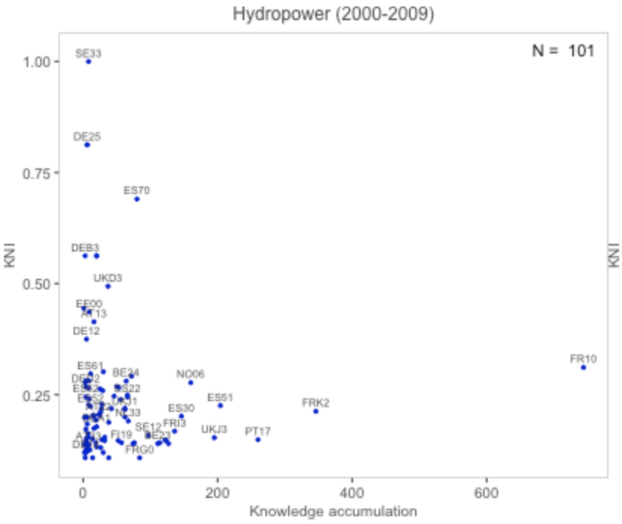


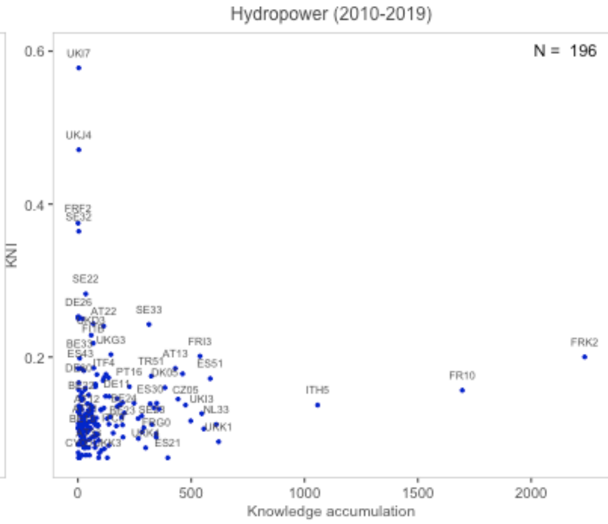


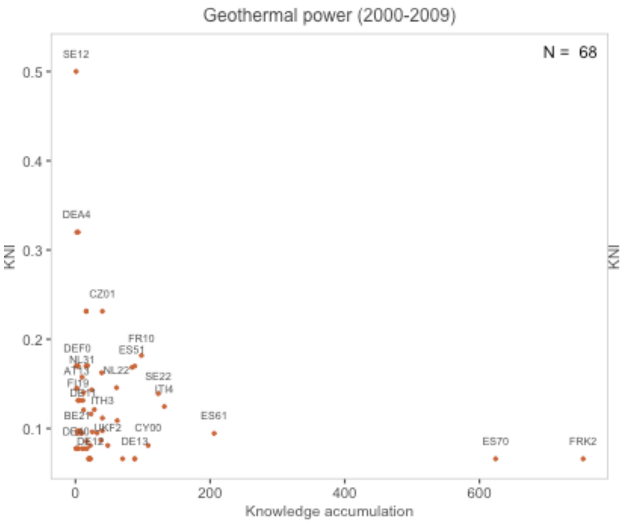


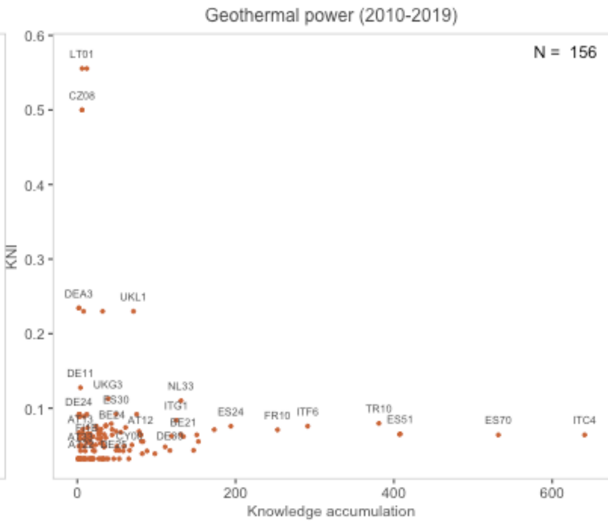

Wind power (2000-2009)
N = 188
Wind power (2010-2019)
N = 257
Concentrated solar power (CSP) (2000-2009)
N = 189
Concentrated solar power (CSP) (2010-2019)
N = 257
Ocean energy (2000-2009)
N = 135
Ocean energy (2010-2019)
N = 209
KNI
Technological and infrastructural carbon lock-in

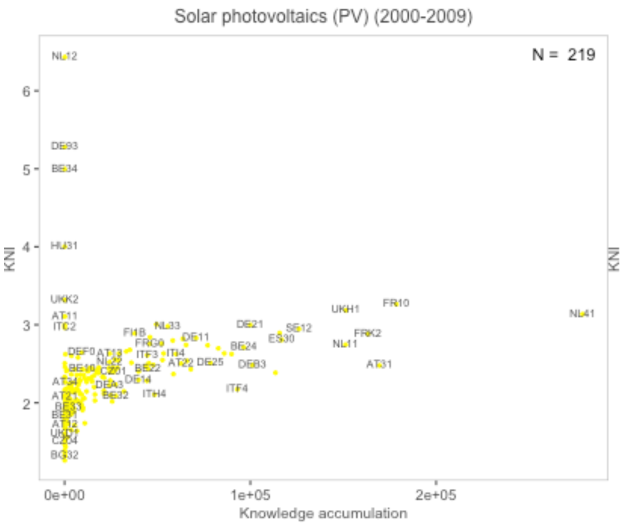
D.3 Knowledge accumulation (2000-2009; 2010-2019)

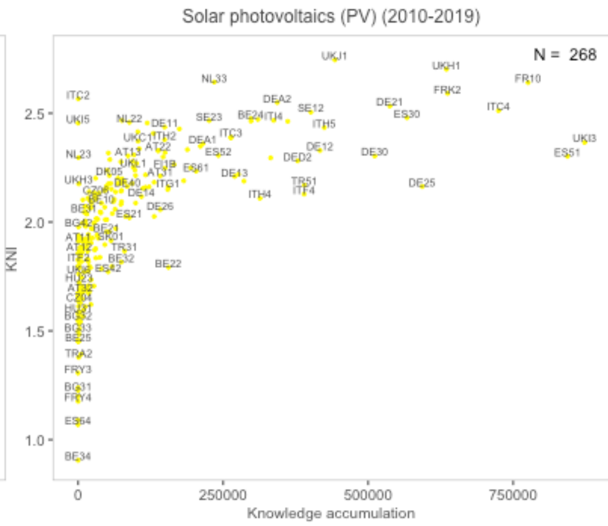


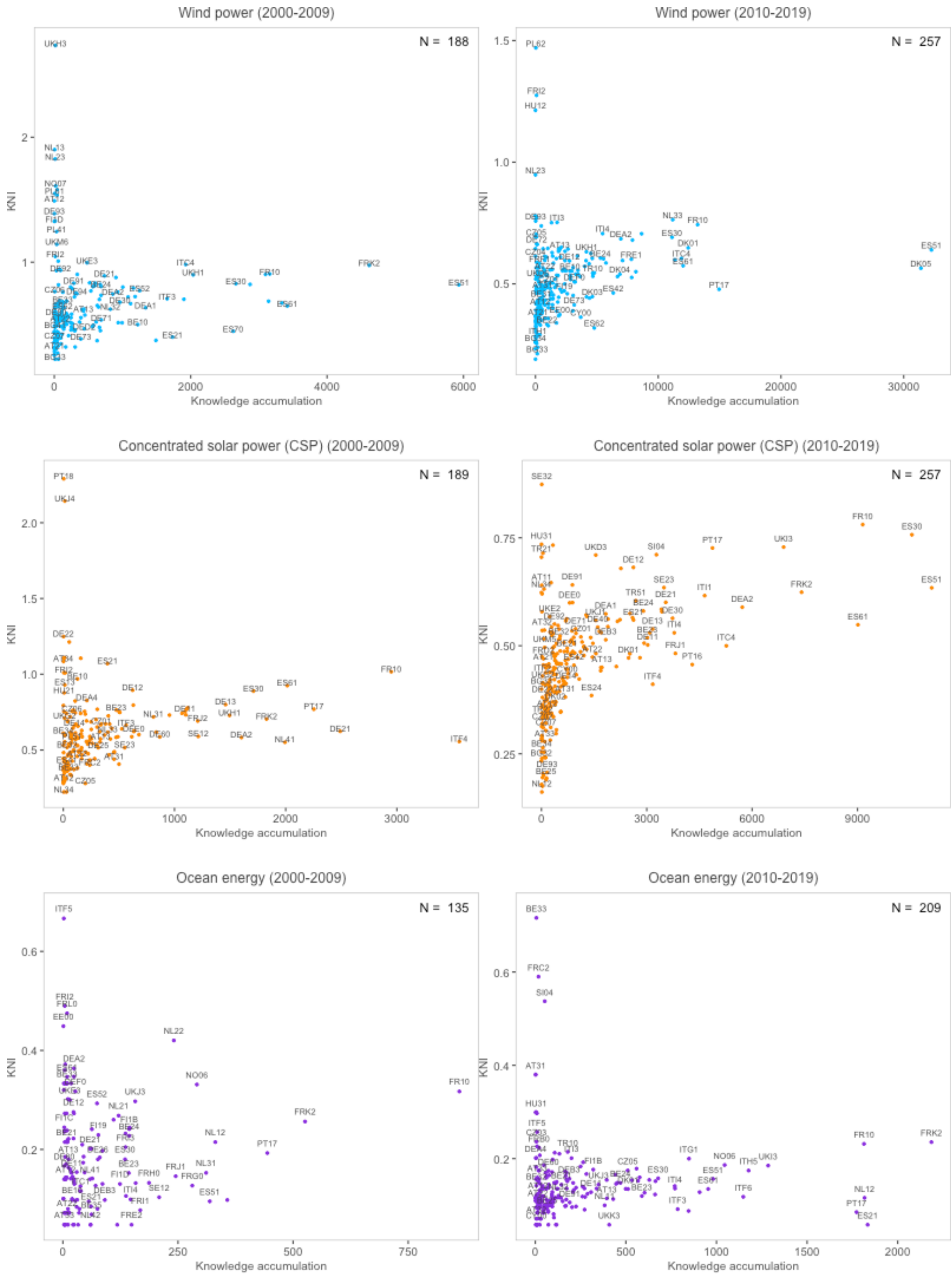




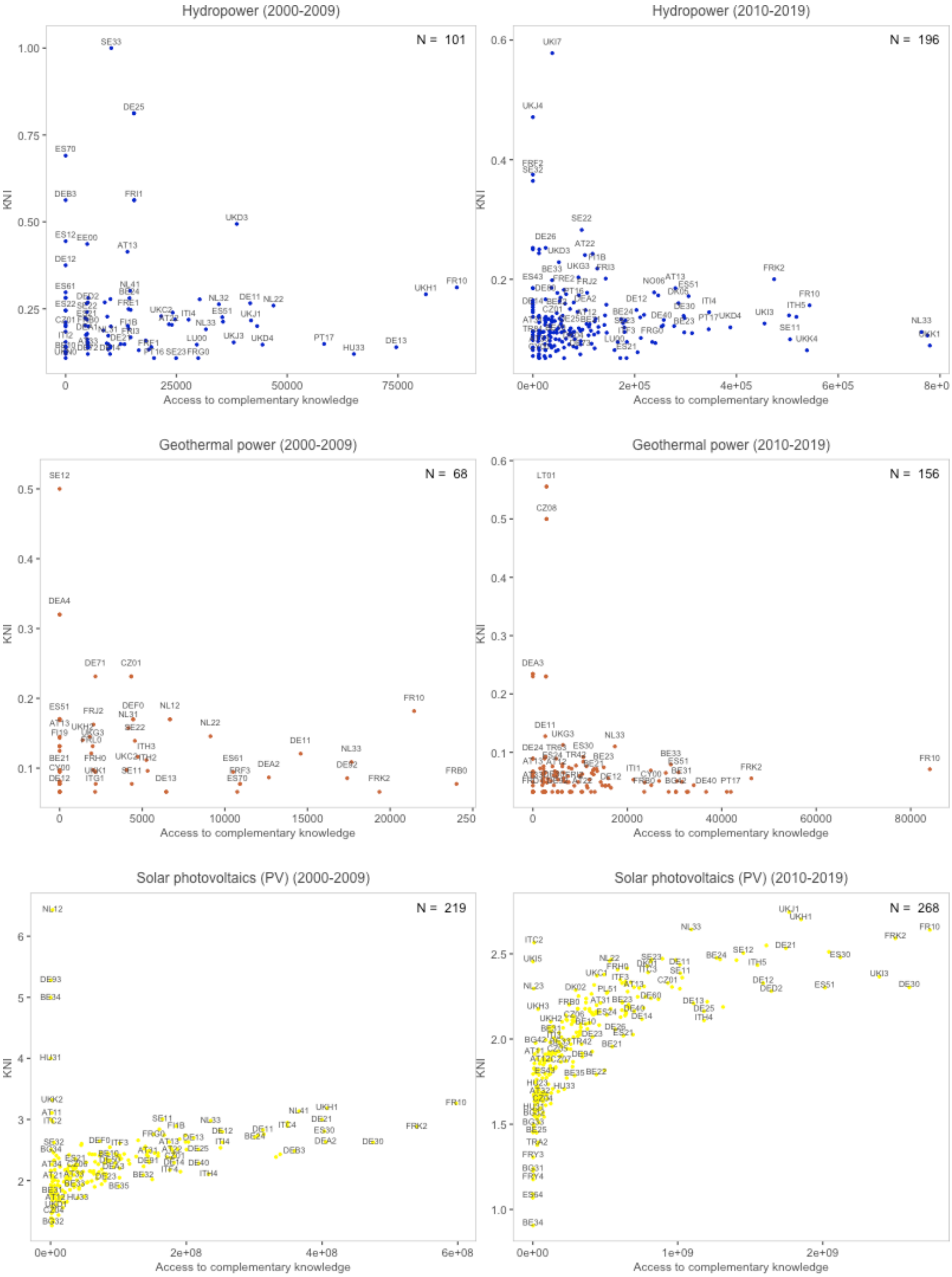


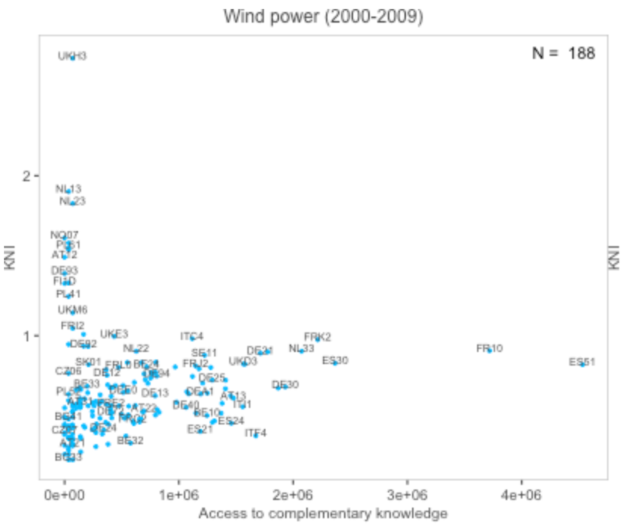


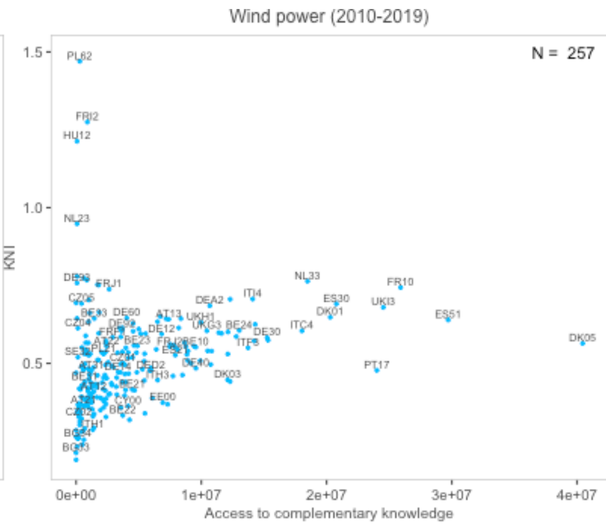


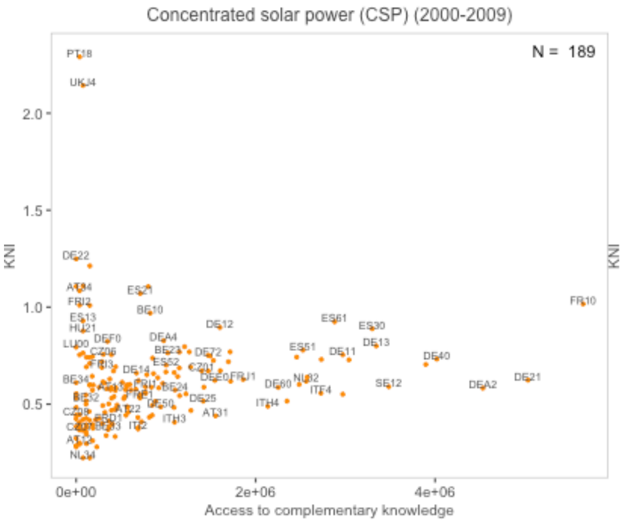

Wind power (2000-2009)
N = 188
KNI
Knowledge accumulation
Wind power (2010-2019)
N = 257
KNI
Knowledge accumulation
Concentrated solar power (CSP) (2000-2009)
N = 189
KNI
Knowledge accumulation
Concentrated solar power (CSP) (2010-2019)
N = 257
KNI
Knowledge accumulation
Ocean energy (2000-2009)
N = 135
KNI
Knowledge accumulation
Ocean energy (2010-2019)
N = 209
KNI
Knowledge accumulation

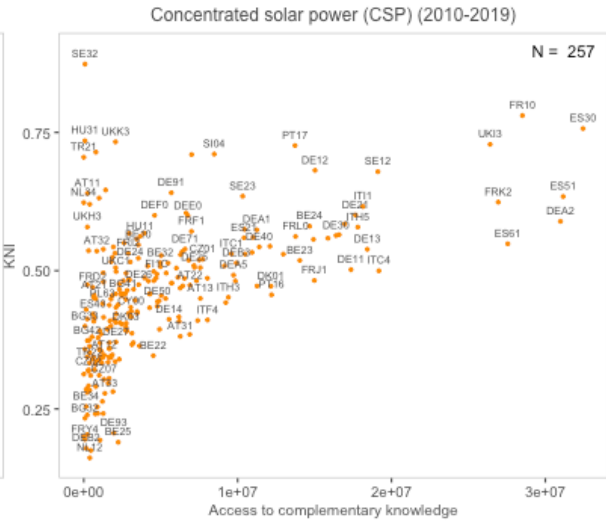
D.4 KNI and access to complementary knowledge (2000-2009; 2010-2019)

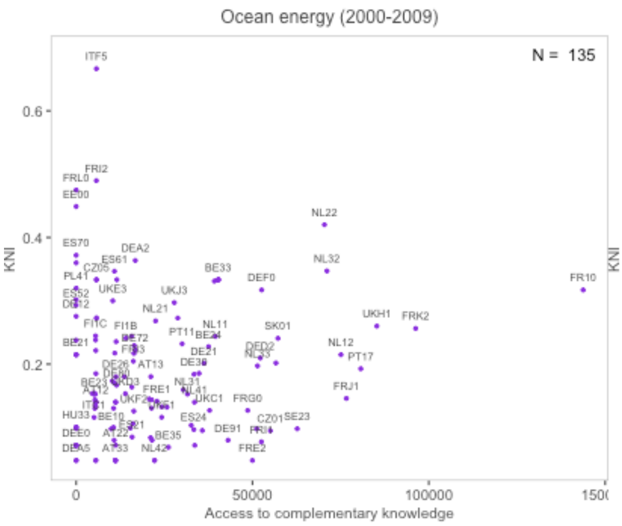


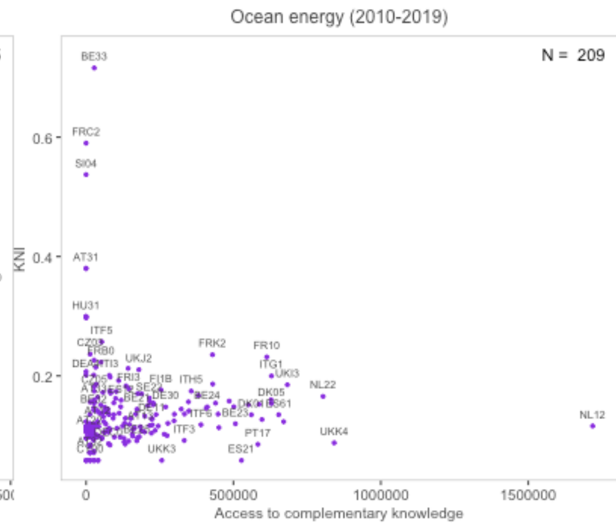

Wind power (2000-2009)
N = 188
KNI
Access to complementary knowledge


Wind power (2010-2019)
N = 257
KNI
Access to complementary knowledge

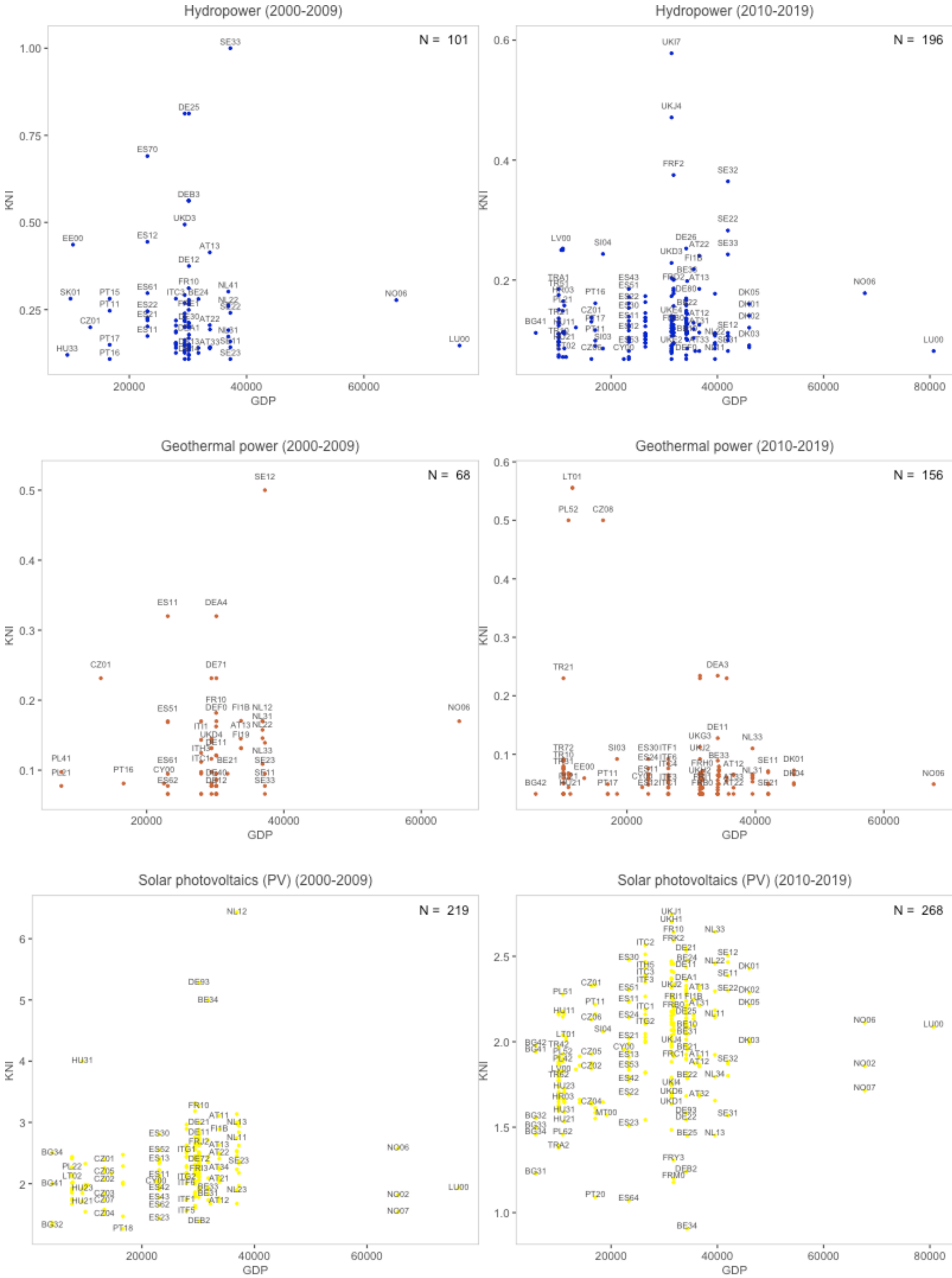

Concentrated solar power (CSP) (2000-2009)
N = 189
KNI
Access to complementary knowledge

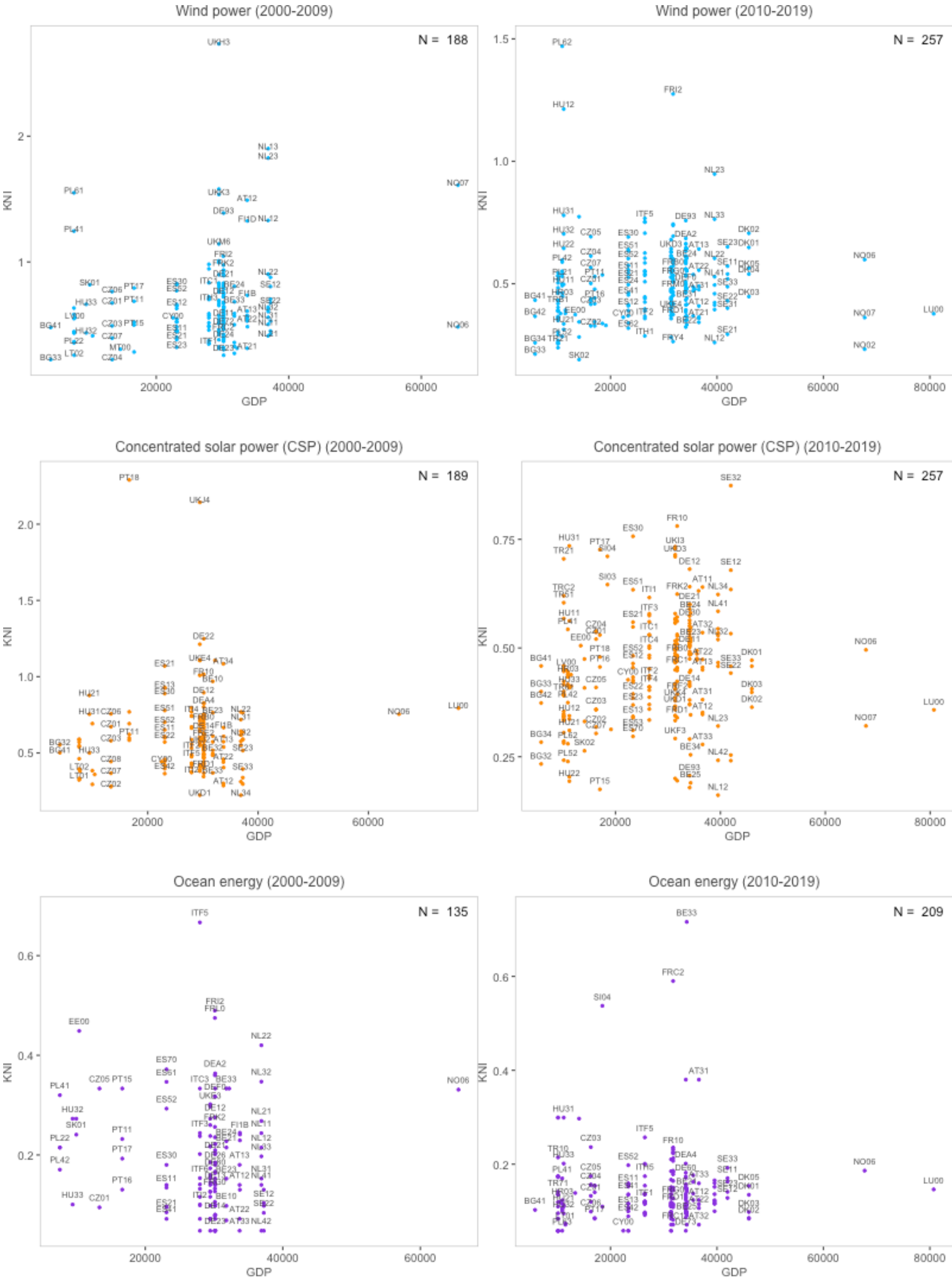

Concentrated solar power (CSP) (2010-2019)
N = 257
KNI
Access to complementary knowledge


Ocean energy (2000-2009)
N = 135
KNI
Access to complementary knowledge


Ocean energy (2010-2019)
N = 209
KNI
Access to complementary knowledge

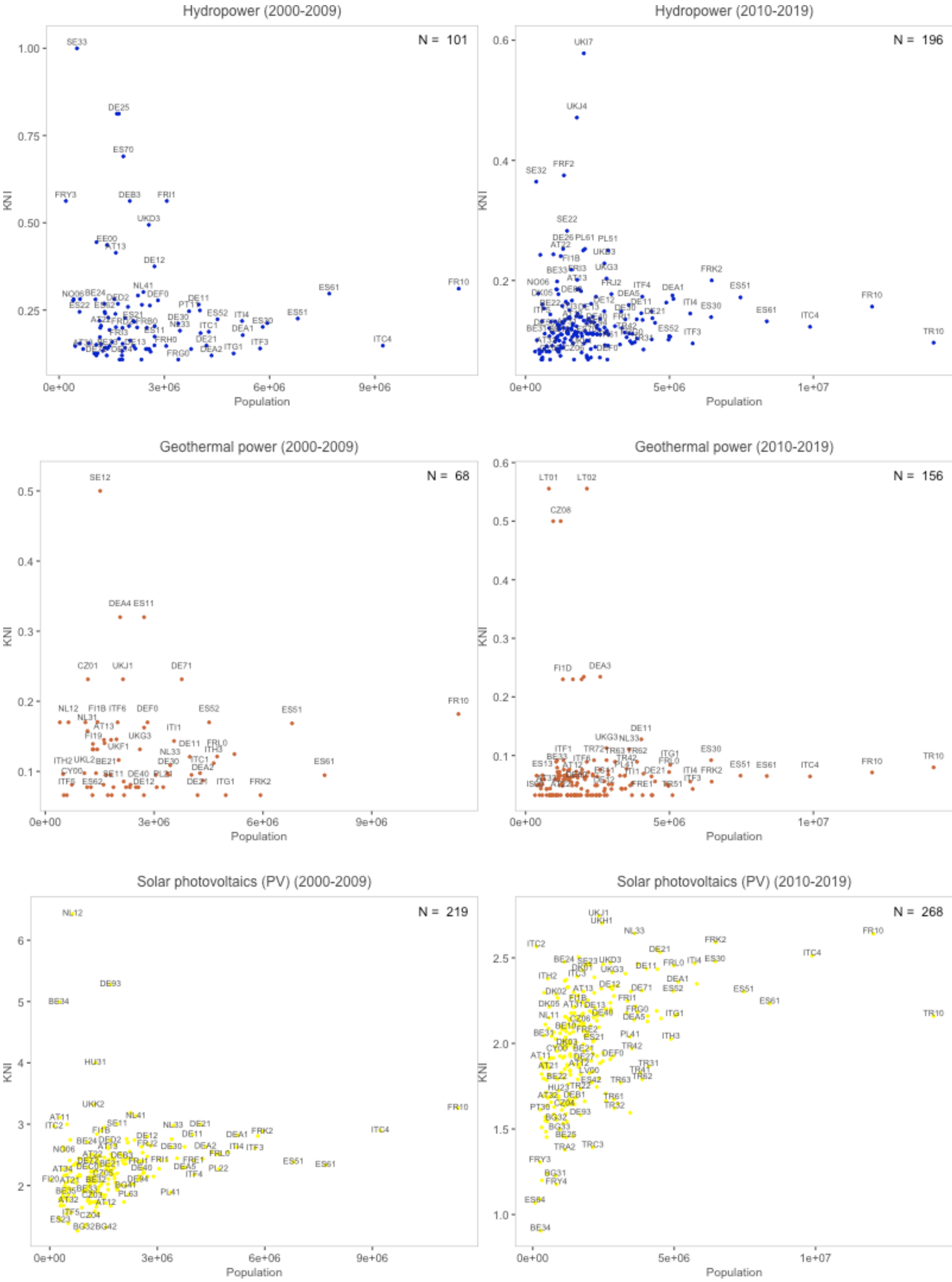
D.5 KNI and GDP (2000-2009; 2010-2019)

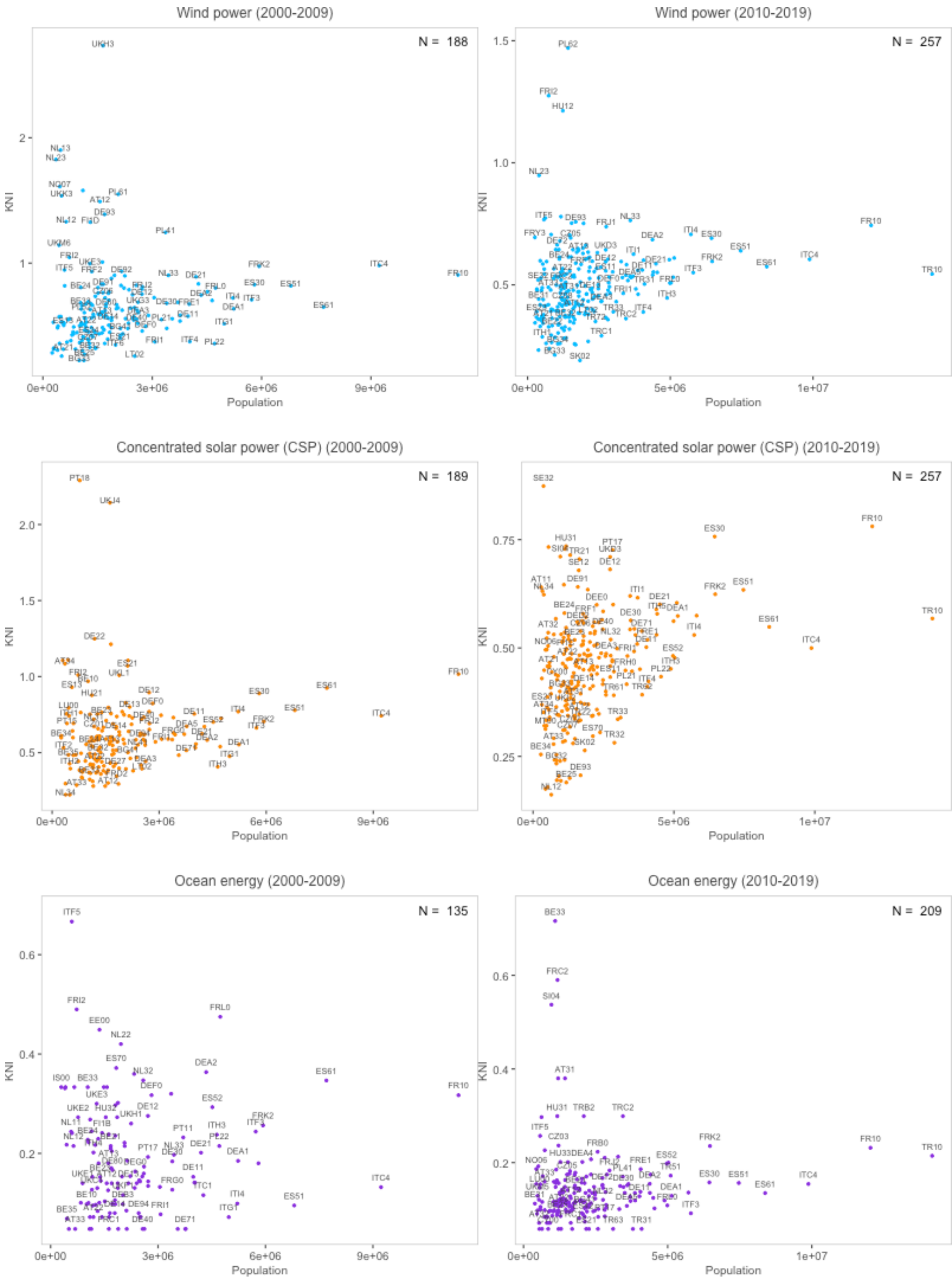




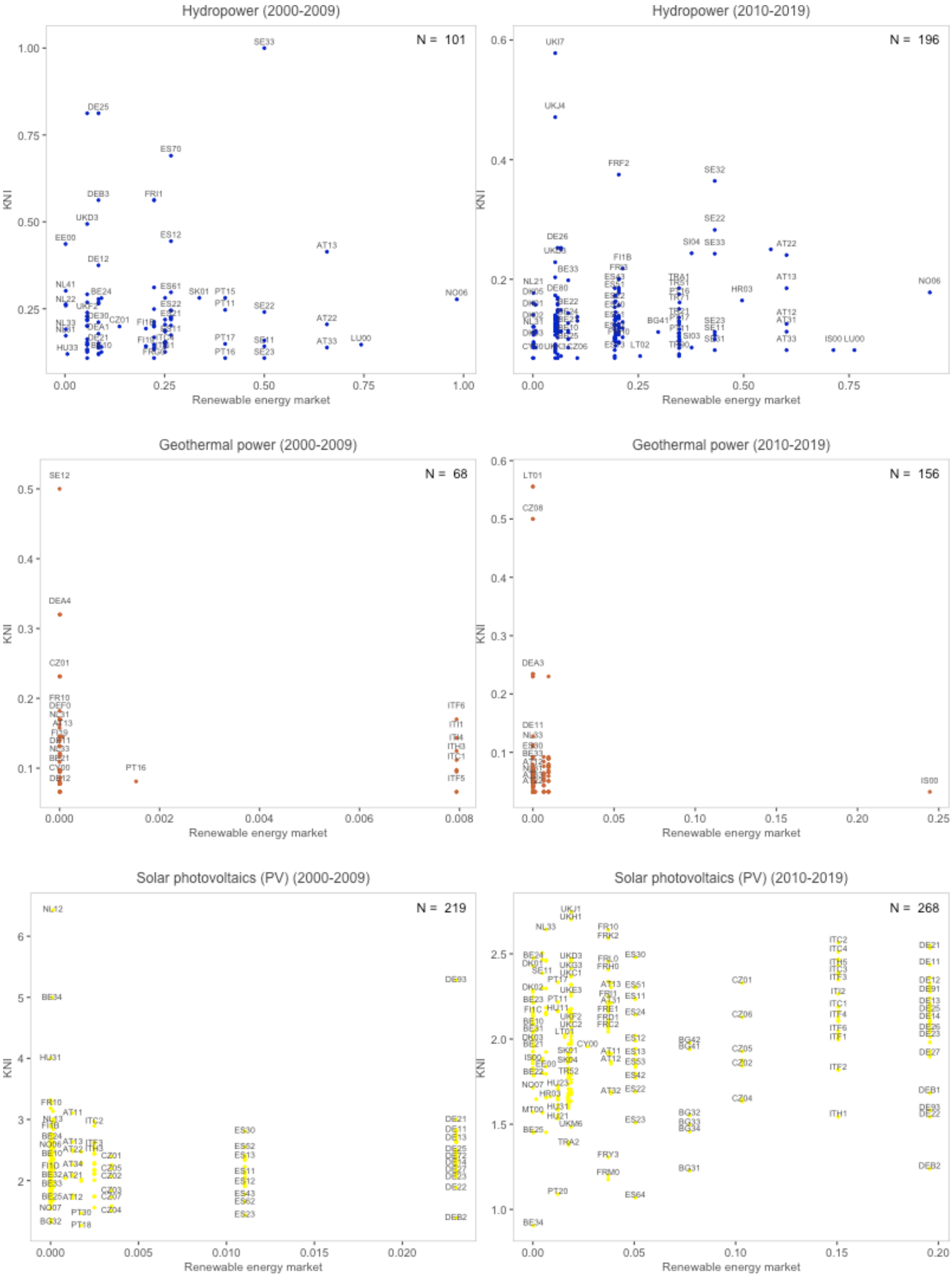
Wind power (2000-2009)
N = 188
Wind power (2010-2019)
N = 257
Concentrated solar power (CSP) (2000-2009)
N = 189
Concentrated solar power (CSP) (2010-2019)
N = 257
Ocean energy (2000-2009)
N = 135
Ocean energy (2010-2019)
N = 209
KNI
GDP

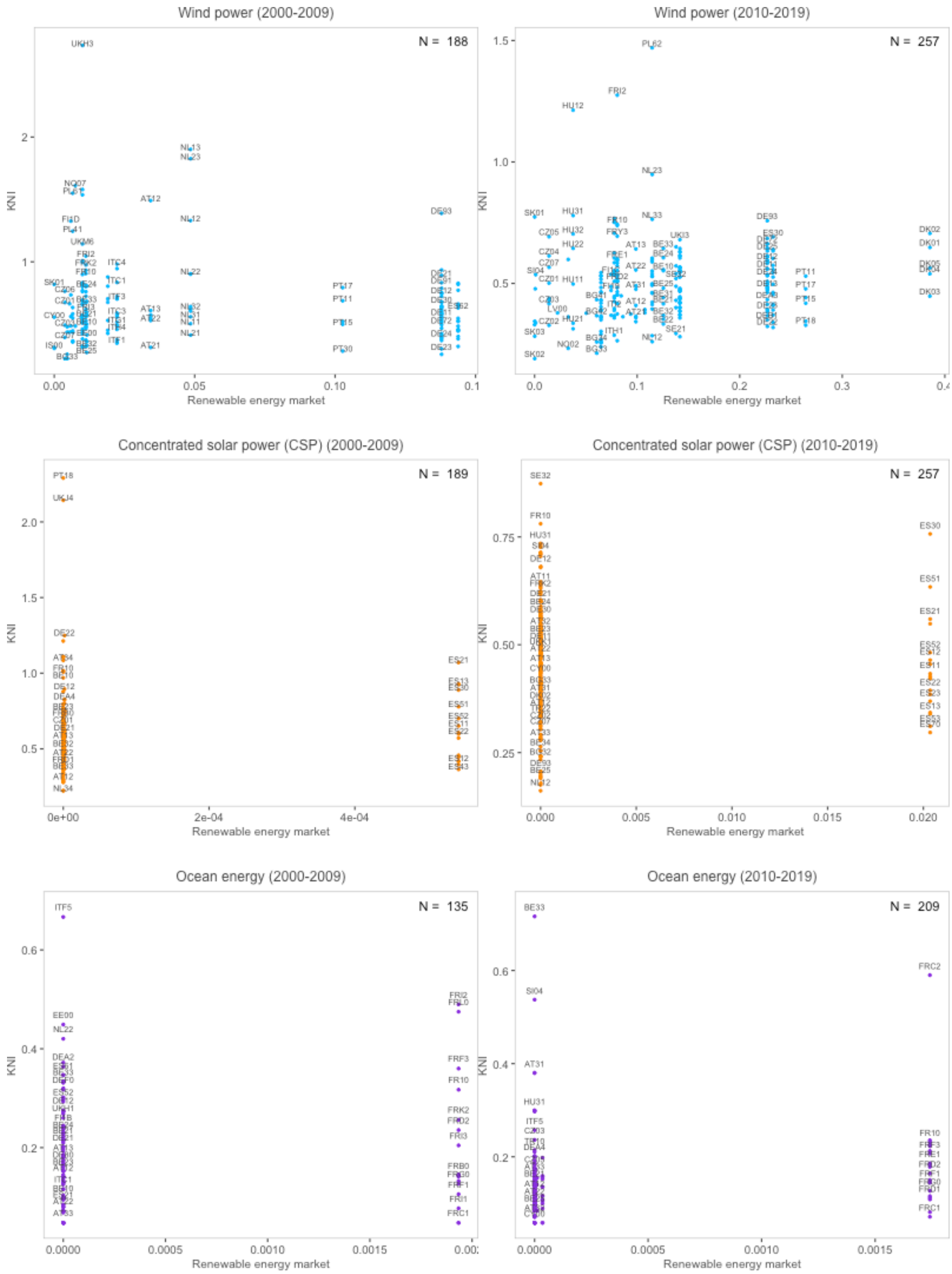
D.6 KNI and population (2000-2009; 2010-2019)




Wind power (2000-2009)
N = 188
Wind power (2010-2019)
N = 257
Concentrated solar power (CSP) (2000-2009)
N = 189
Concentrated solar power (CSP) (2010-2019)
N = 257
Ocean energy (2000-2009)
N = 135
Ocean energy (2010-2019)
N = 209
KNI
Population

D.7 KNI and renewable energy market (2000-2009; 2010-2019)




Wind power (2000-2009)
N = 188
KNI
Renewable energy market
0.00
0.05
0.10
Wind power (2010-2019)
N = 257
KNI
Renewable energy market
0.0
0.1
0.2
0.3
Concentrated solar power (CSP) (2000-2009)
N = 189
KNI
Renewable energy market
0e+00
2e-04
4e-04
Concentrated solar power (CSP) (2010-2019)
N = 257
KNI
Renewable energy market
0.000
0.005
0.010
0.015
0.020
Ocean energy (2000-2009)
N = 135
KNI
Renewable energy market
0.0000
0.0005
0.0010
0.0015
Ocean energy (2010-2019)
N = 209
KNI
Renewable energy market
0.0000
0.0005
0.0010
0.0015

Appendix E. Correlation matrices

E.1 Hydropower

2000-2009	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	-0.14	-0.05	-0.09	-0.02	-0.02	-0.10	0.04
RD	-0.14	1.00	0.23	0.15	0.43	0.09	0.29	-0.14
K	-0.05	0.23	1.00	-0.23	0.56	0.03	0.56	0.10
C	-0.09	0.15	-0.23	1.00	-0.01	-0.22	0.01	-0.51
CL	-0.02	0.43	0.56	-0.01	1.00	0.09	0.24	-0.06
GDP	-0.02	0.09	0.03	-0.22	0.09	1.00	-0.14	0.36
P	-0.10	0.29	0.56	0.01	0.24	-0.14	1.00	-0.07
M	0.04	-0.14	0.10	-0.51	-0.06	0.36	-0.07	1.00

2010-2019	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	-0.06	0.05	-0.16	-0.07	0.06	0.01	0.06
RD	-0.06	1.00	0.21	-0.01	0.35	0.13	0.36	-0.12
K	0.05	0.21	1.00	-0.20	0.70	0.13	0.42	0.06
C	-0.16	-0.01	-0.20	1.00	-0.10	-0.40	0.07	-0.43
CL	-0.07	0.35	0.70	-0.10	1.00	0.26	0.26	-0.03
GDP	0.06	0.13	0.13	-0.40	0.26	1.00	-0.21	-0.04
P	0.01	0.36	0.42	0.07	0.26	-0.21	1.00	0.02
M	0.06	-0.12	0.06	-0.43	-0.03	-0.04	0.02	1.00

E.2 Geothermal

2000-2009	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	0.03	0.24	0.00	0.17	0.27	0.09	-0.11
RD	0.03	1.00	0.71	-0.26	0.40	-0.08	0.77	-0.09
K	0.24	0.71	1.00	-0.28	0.39	0.05	0.67	-0.06
C	0.00	-0.26	-0.28	1.00	-0.20	-0.36	-0.18	0.27
CL	0.17	0.40	0.39	-0.20	1.00	0.08	0.45	-0.17
GDP	0.27	-0.08	0.05	-0.36	0.08	1.00	-0.21	-0.10
P	0.09	0.77	0.67	-0.18	0.45	-0.21	1.00	0.07
M	-0.11	-0.09	-0.06	0.27	-0.17	-0.10	0.07	1.00

2010-2019	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	-0.05	-0.04	0.11	-0.15	-0.22	-0.05	-0.05
RD	-0.05	1.00	0.29	-0.01	0.19	0.19	0.28	-0.07
K	-0.04	0.29	1.00	0.00	0.20	-0.02	0.59	-0.02
C	0.11	-0.01	0.00	1.00	-0.16	-0.47	0.04	-0.09
CL	-0.15	0.19	0.20	-0.16	1.00	0.13	0.25	-0.04
GDP	-0.22	0.19	-0.02	-0.47	0.13	1.00	-0.19	-0.05
P	-0.05	0.28	0.59	0.04	0.25	-0.19	1.00	-0.04
M	-0.05	-0.07	-0.02	-0.09	-0.04	-0.05	-0.04	1.00

E.3 Solar photovoltaics

2000-2009	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	0.29	0.36	-0.01	0.37	0.23	0.25	0.12
RD	0.29	1.00	0.51	-0.04	0.78	0.14	0.72	0.19
K	0.36	0.51	1.00	-0.01	0.86	0.18	0.52	0.15
C	-0.01	-0.04	-0.01	1.00	-0.05	-0.29	0.03	0.13
CL	0.37	0.78	0.86	-0.05	1.00	0.17	0.64	0.25
GDP	0.23	0.14	0.18	-0.29	0.17	1.00	-0.09	0.08
P	0.25	0.72	0.52	0.03	0.64	-0.09	1.00	0.16
M	0.12	0.19	0.15	0.13	0.25	0.08	0.16	1.00

	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	0.74	0.61	-0.03	0.70	0.33	0.45	0.19
RD	0.74	1.00	0.51	-0.09	0.67	0.16	0.58	0.19
K	0.61	0.51	1.00	-0.02	0.94	0.15	0.56	0.23
C	-0.03	-0.09	-0.02	1.00	-0.06	-0.39	0.09	0.15
CL	0.70	0.67	0.94	-0.06	1.00	0.21	0.56	0.27
GDP	0.33	0.16	0.15	-0.39	0.21	1.00	-0.15	0.12
P	0.45	0.58	0.56	0.09	0.56	-0.15	1.00	0.15
M	0.19	0.19	0.23	0.15	0.27	0.12	0.15	1.00

E.4 Wind power

2000-2009	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	0.10	0.10	0.07	0.06	0.22	0.10	-0.09
RD	0.10	1.00	0.54	-0.04	0.77	0.22	0.63	0.16
K	0.10	0.54	1.00	-0.06	0.78	0.06	0.65	0.11
C	0.07	-0.04	-0.06	1.00	-0.07	-0.35	0.02	0.14
CL	0.06	0.77	0.78	-0.07	1.00	0.19	0.64	0.16
GDP	0.22	0.22	0.06	-0.35	0.19	1.00	-0.08	0.06
P	0.10	0.63	0.65	0.02	0.64	-0.08	1.00	0.12
M	-0.09	0.16	0.11	0.14	0.16	0.06	0.12	1.00

2010-2019	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	0.33	0.24	-0.03	0.28	0.11	0.21	0.11
RD	0.33	1.00	0.47	-0.05	0.69	0.23	0.57	0.21
K	0.24	0.47	1.00	-0.05	0.90	0.16	0.46	0.35
C	-0.03	-0.05	-0.05	1.00	-0.05	-0.41	0.10	0.07
CL	0.28	0.69	0.90	-0.05	1.00	0.24	0.48	0.40
GDP	0.11	0.23	0.16	-0.41	0.24	1.00	-0.16	0.34
P	0.21	0.57	0.46	0.10	0.48	-0.16	1.00	0.01
M	0.11	0.21	0.35	0.07	0.40	0.34	0.01	1.00

E.5 Concentrated solar power

	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	0.15	0.16	0.01	0.15	0.09	0.14	0.03
RD	0.15	1.00	0.60	0.00	0.76	0.14	0.68	0.04
K	0.16	0.60	1.00	0.00	0.86	0.11	0.60	0.05
C	0.01	0.00	0.00	1.00	-0.02	-0.25	0.03	0.03
CL	0.15	0.76	0.86	-0.02	1.00	0.18	0.60	0.01
GDP	0.09	0.14	0.11	-0.25	0.18	1.00	-0.08	-0.13
P	0.14	0.68	0.60	0.03	0.60	-0.08	1.00	0.13
M	0.03	0.04	0.05	0.03	0.01	-0.13	0.13	1.00

2010-2019	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	0.57	0.50	-0.11	0.54	0.18	0.34	-0.01
RD	0.57	1.00	0.66	-0.05	0.77	0.19	0.60	0.01
K	0.50	0.66	1.00	-0.09	0.93	0.10	0.64	0.23
C	-0.11	-0.05	-0.09	1.00	-0.11	-0.39	0.08	-0.07
CL	0.54	0.77	0.93	-0.11	1.00	0.20	0.59	0.14
GDP	0.18	0.19	0.10	-0.39	0.20	1.00	-0.15	-0.09
P	0.34	0.60	0.64	0.08	0.59	-0.15	1.00	0.11
M	-0.01	0.01	0.23	-0.07	0.14	-0.09	0.11	1.00

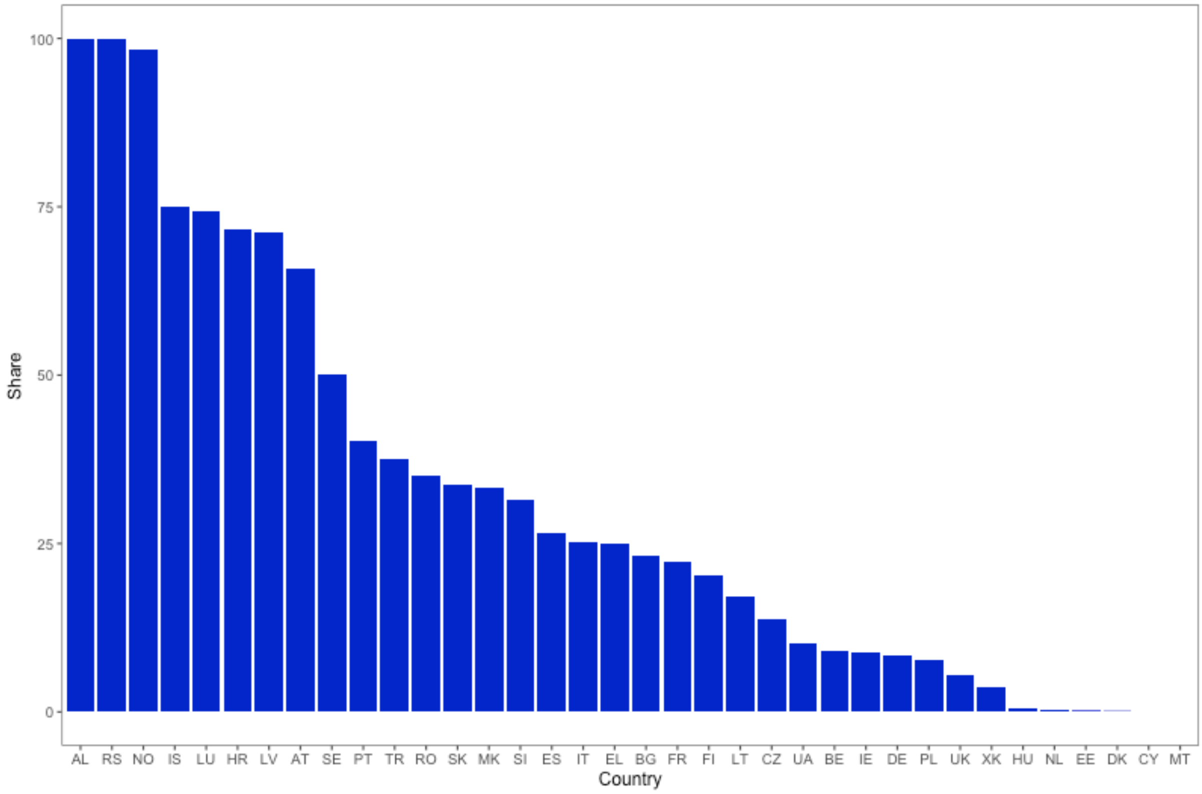
E.6 Ocean energy

2000-2009	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	-0.02	0.03	0.05	0.09	-0.10	0.02	0.06
RD	-0.02	1.00	0.44	-0.08	0.46	0.19	0.29	0.03
K	0.03	0.44	1.00	-0.26	0.75	0.20	0.40	0.31
C	0.05	-0.08	-0.26	1.00	-0.19	-0.30	0.02	-0.65
CL	0.09	0.46	0.75	-0.19	1.00	0.18	0.19	0.22
GDP	-0.10	0.19	0.20	-0.30	0.18	1.00	-0.14	0.08
P	0.02	0.29	0.40	0.02	0.19	-0.14	1.00	0.20
M	0.06	0.03	0.31	-0.65	0.22	0.08	0.20	1.00

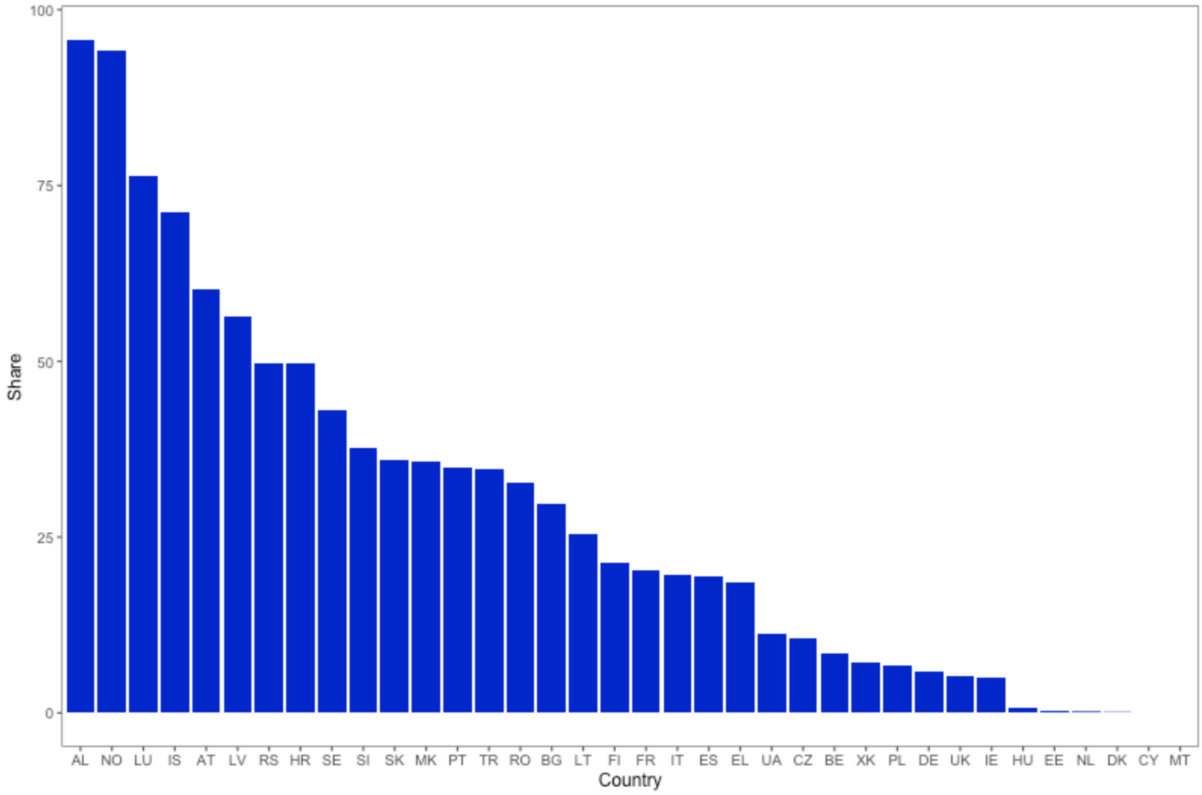
2010-2019	KNI	RD	K	C	CL	GDP	P	M
KNI	1.00	0.00	0.01	-0.24	-0.03	0.04	0.06	0.18
RD	0.00	1.00	0.35	-0.02	0.41	0.21	0.42	-0.01
K	0.01	0.35	1.00	-0.10	0.78	0.17	0.37	0.11
C	-0.24	-0.02	-0.10	1.00	0.06	-0.36	0.07	-0.62
CL	-0.03	0.41	0.78	0.06	1.00	0.27	0.23	0.01
GDP	0.04	0.21	0.17	-0.36	0.27	1.00	-0.19	0.12
P	0.06	0.42	0.37	0.07	0.23	-0.19	1.00	0.16
M	0.18	-0.01	0.11	-0.62	0.01	0.12	0.16	1.00

Appendix F. Installed capacities

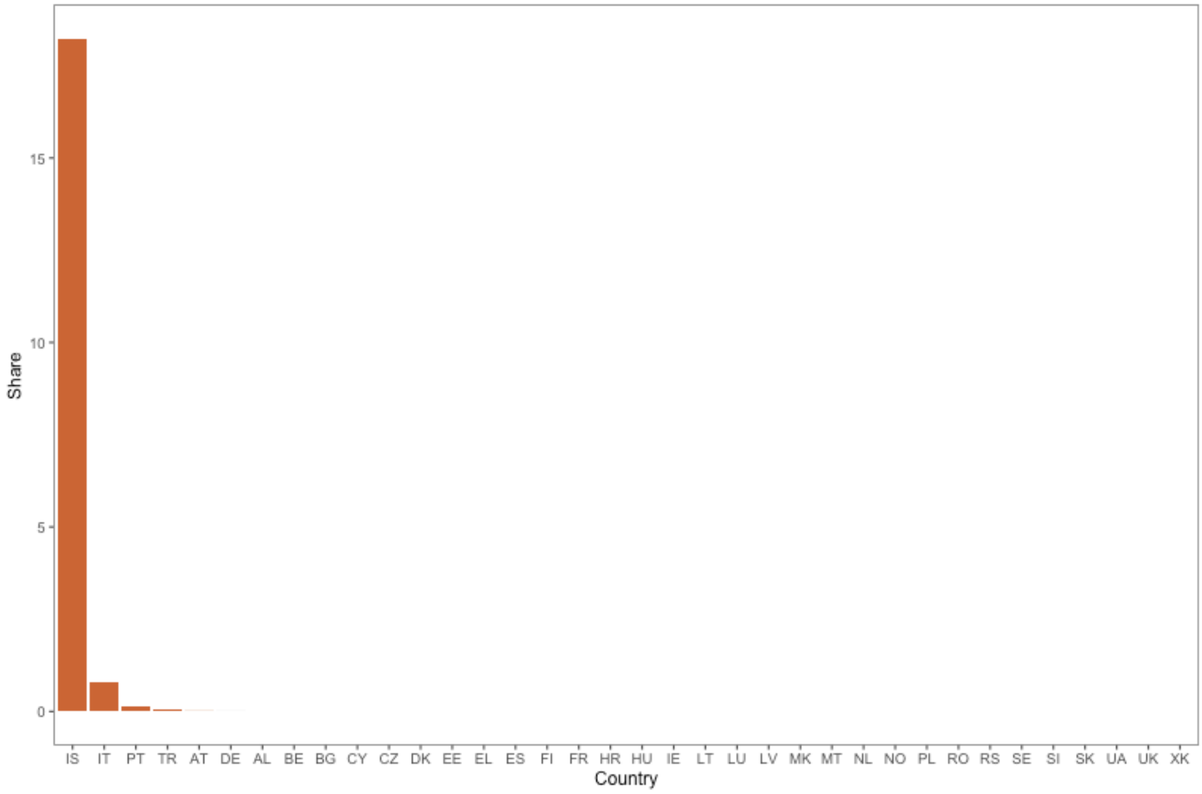
Share of electricity from hydropower (average: 2000-2009)



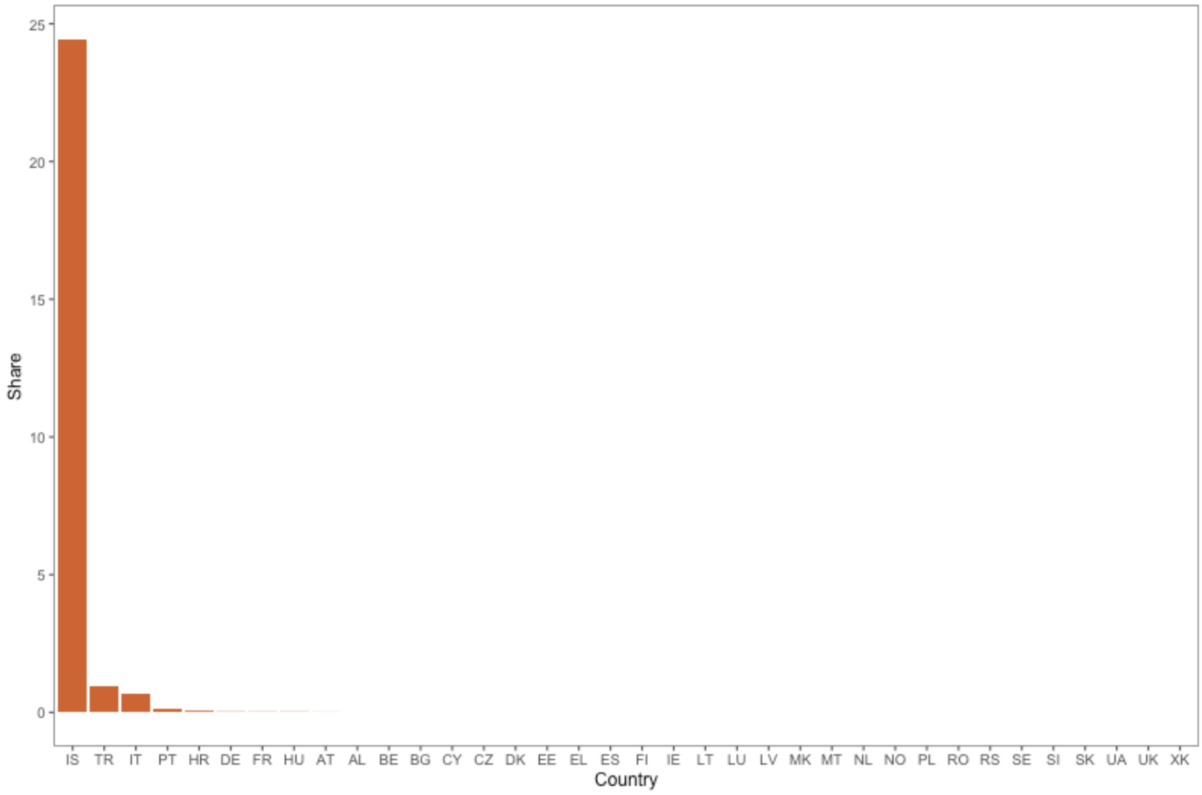
Share of electricity from hydropower (average: 2010-2019)

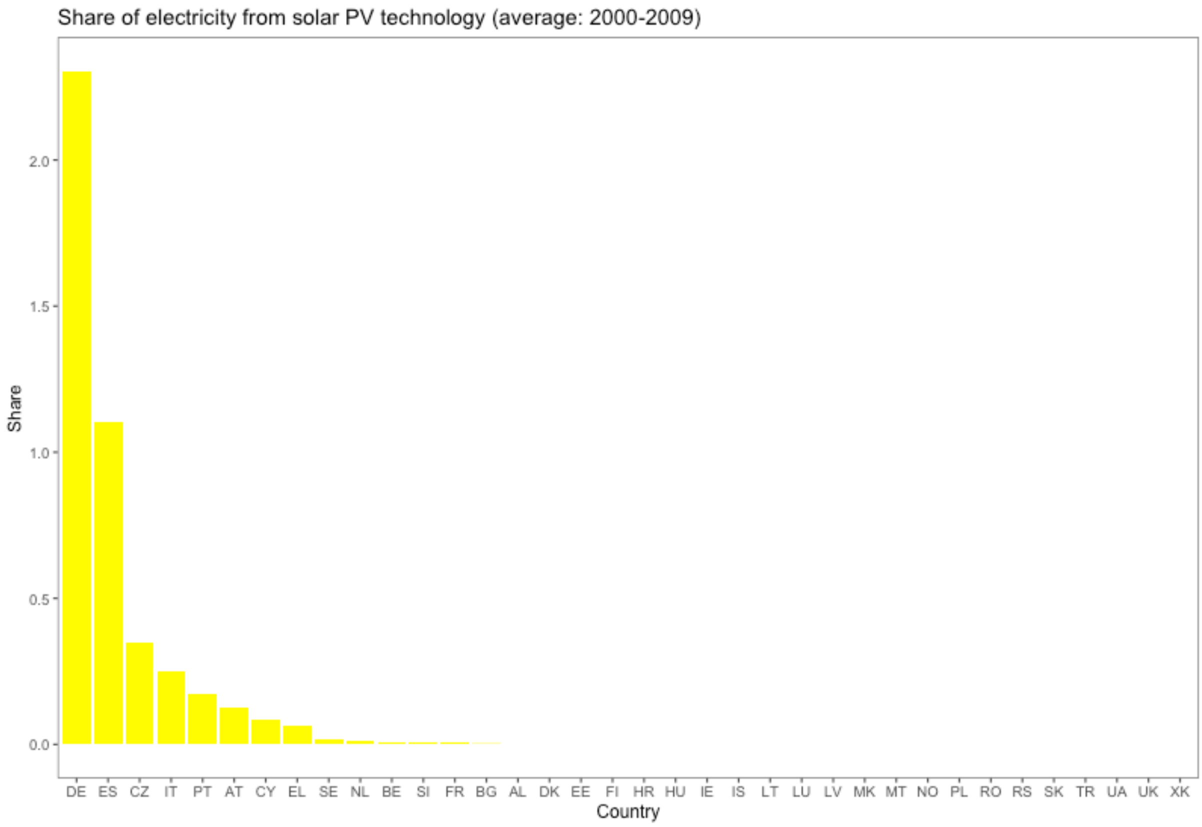


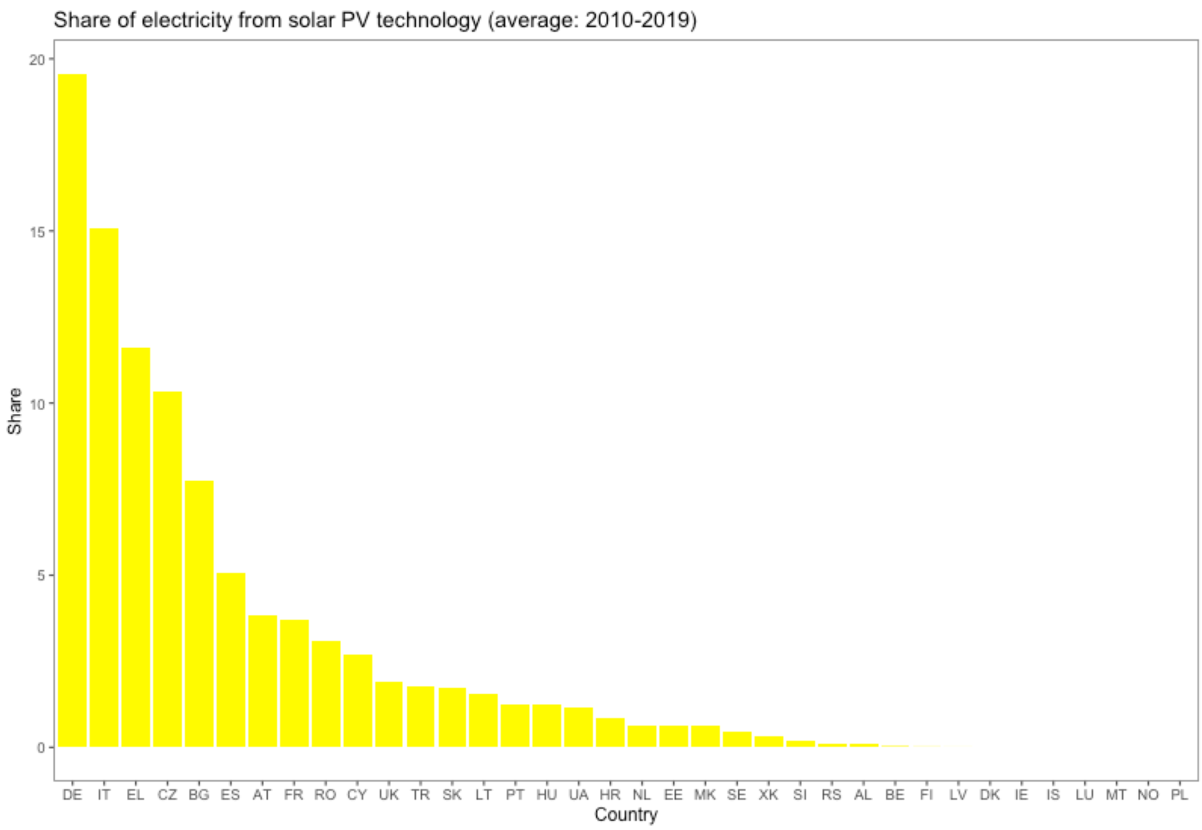
Share of electricity from geothermal power (average: 2000-2009)



Share of electricity from geothermal power (average: 2010-2019)




Share of electricity from solar PV technology (average: 2000-2009)
Share
2.0
1.5
1.0
0.5
0.0
DE ES CZ IT PT AT CY EL SE NL BE SI FR BG AL DK EE FI HR HU IE IS LT LU LV MK MT NO PL RO RS SK TR UA UK XK
Country


Share of electricity from solar PV technology (average: 2010-2019)
Share
20
15
10
5
0
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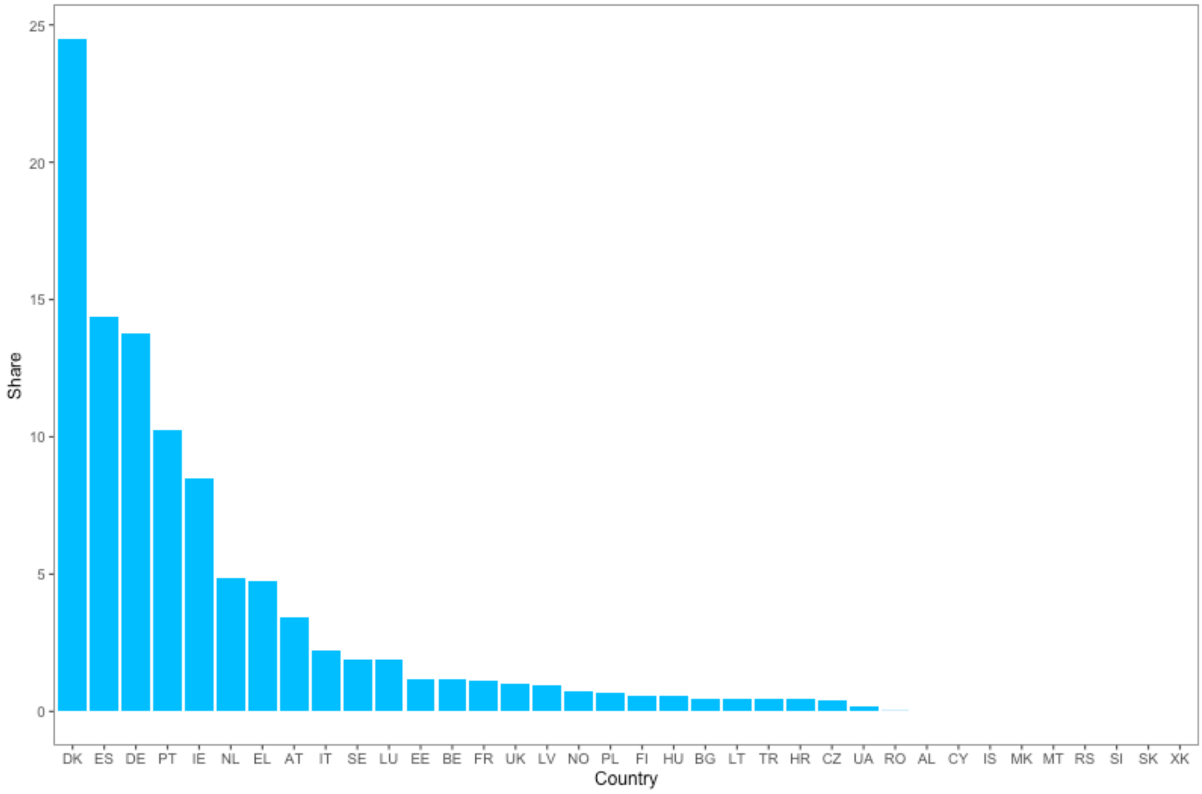
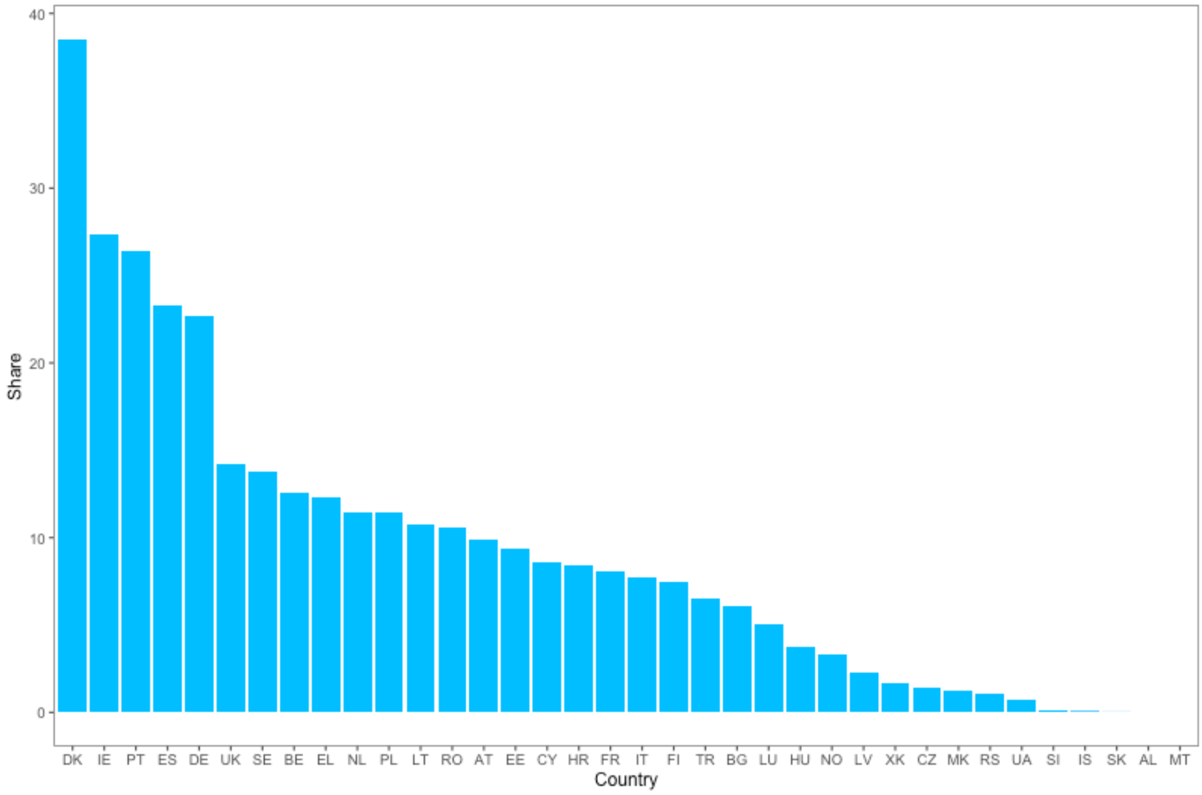
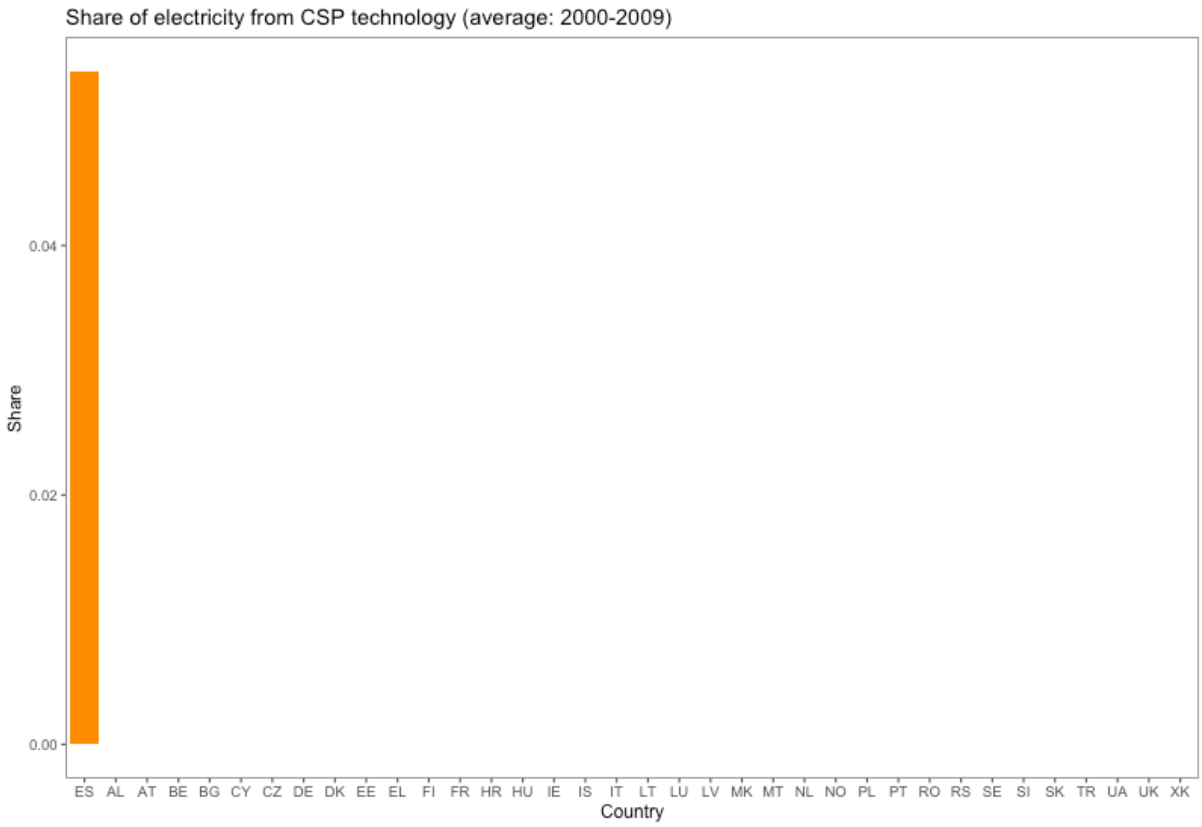
Country

Share of electricity from wind power technology (average: 2000-2009)

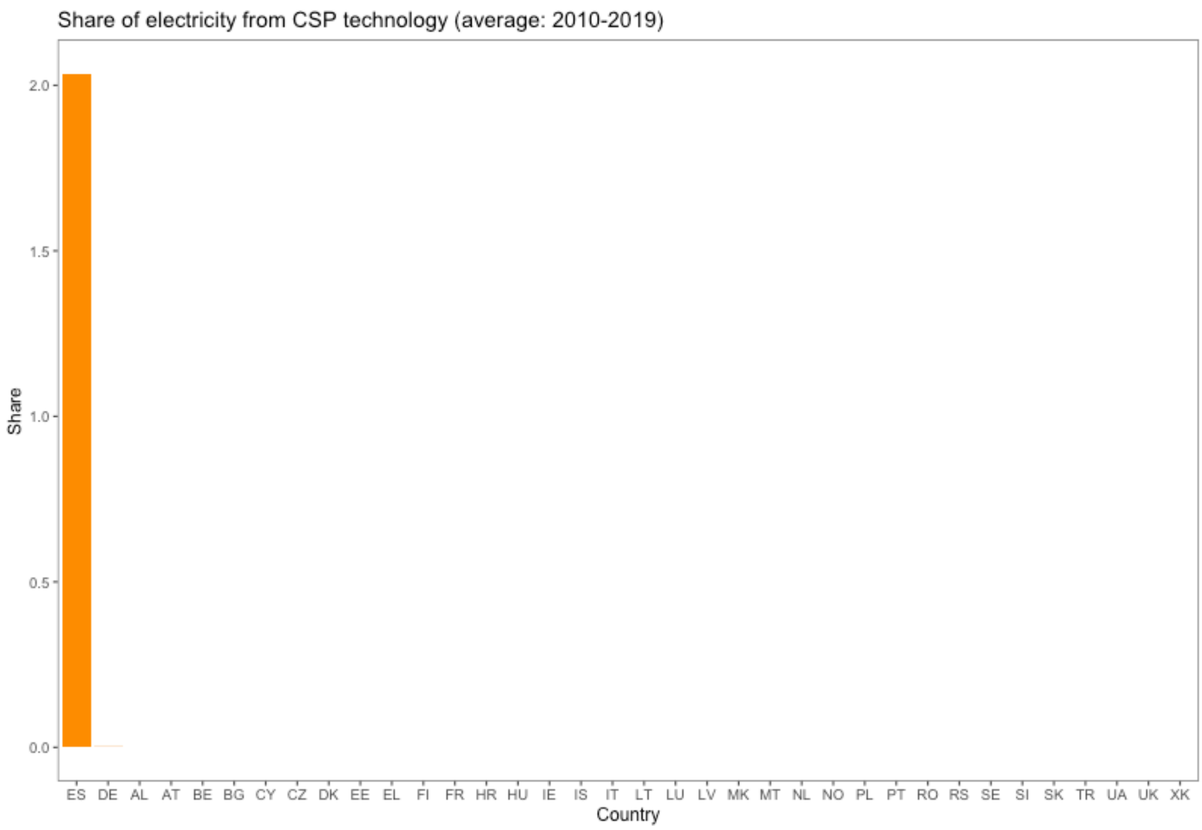


Share of electricity from wind power technology (average: 2010-2019)

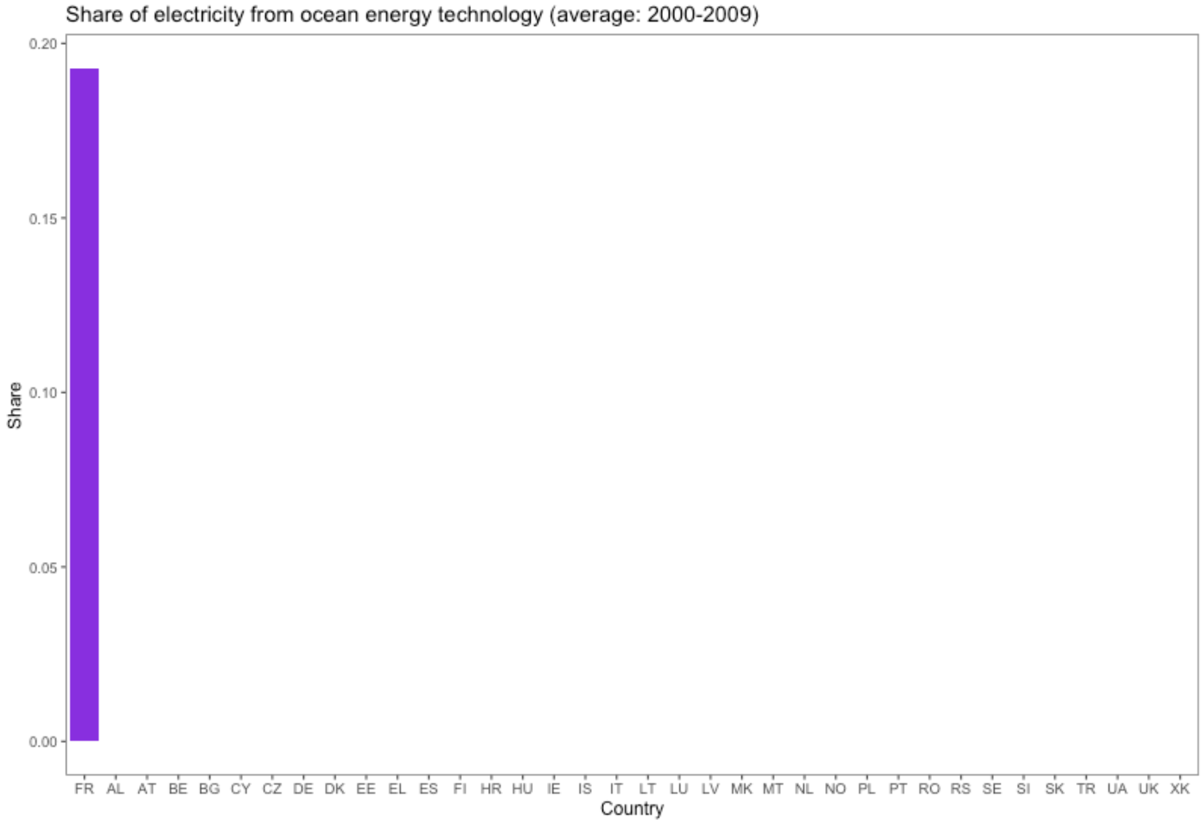




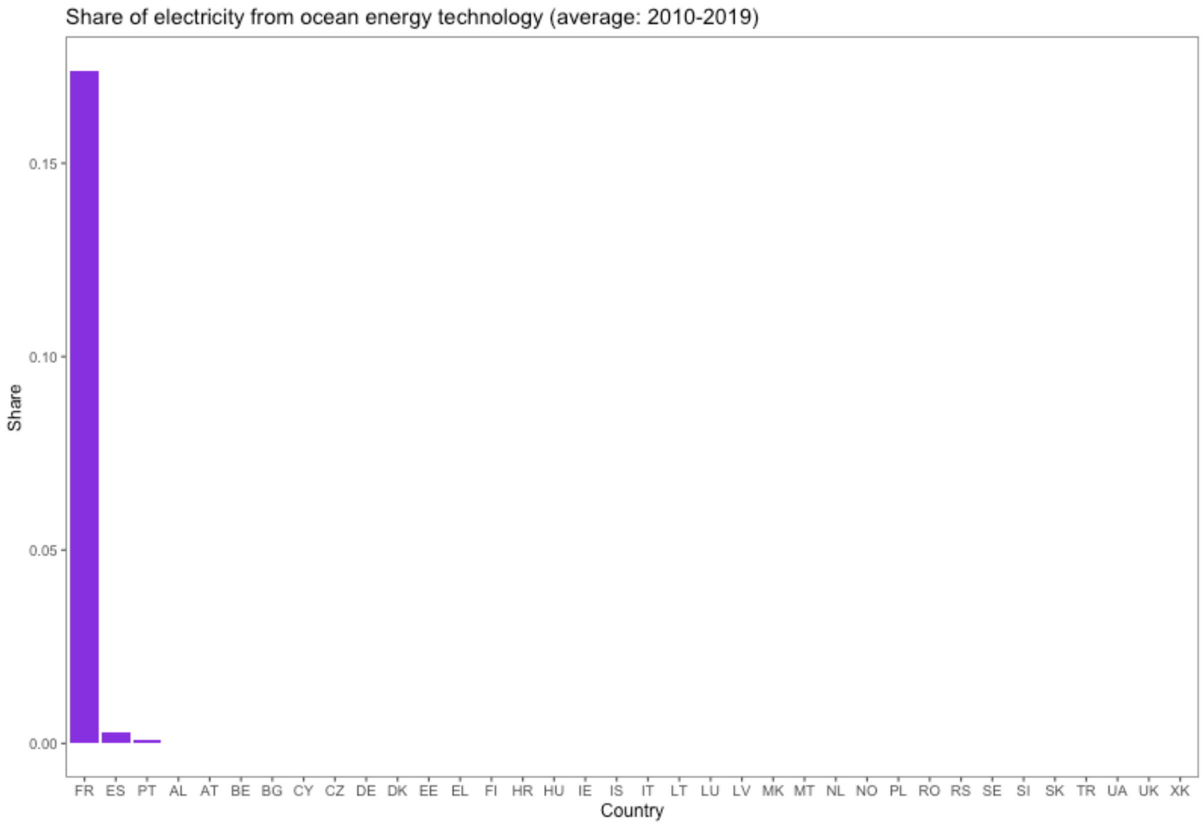
Share of electricity from CSP technology (average: 2000-2009)
0.04
0.02
0.00
Share
ES AL AT BE BG CY CZ DE DK EE EL FI FR HR HU IE IS IT LT LU LV MK MT NL NO PL PT RO RS SE SI SK TR UA UK XK
Country



Share of electricity from CSP technology (average: 2010-2019)
2.0
1.5
1.0
0.5
0.0
Share
ES DE AL AT BE BG CY CZ DK EE EL FI FR HR HU IE IS IT LT LU LV MK MT NL NO PL PT RO RS SE SI SK TR UA UK XK
Country

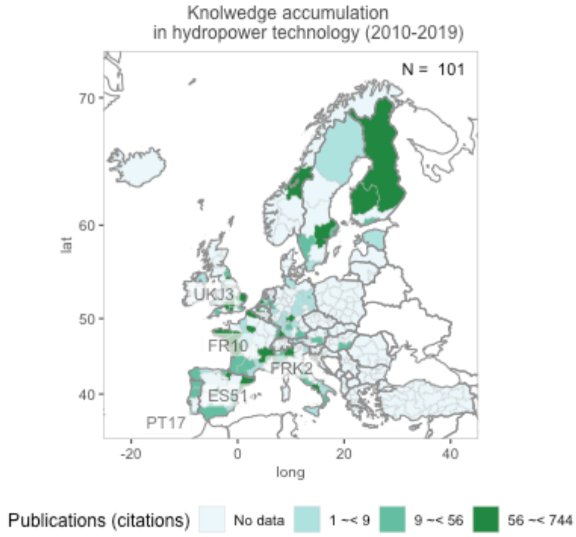


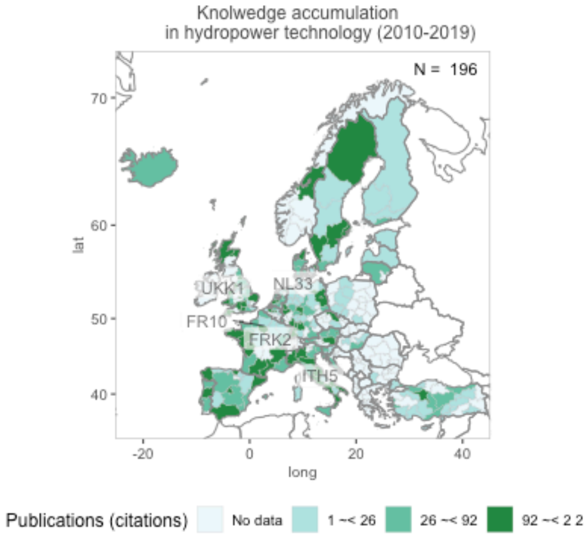
Share of electricity from ocean energy technology (average: 2000-2009)
Share
0.20
0.15
0.10
0.05
0.00
FR AL AT BE BG CY CZ DE DK EE EL ES FI HR HU IE IS IT LT LU LV MK MT NL NO PL PT RO RS SE SI SK TR UA UK XK
Country

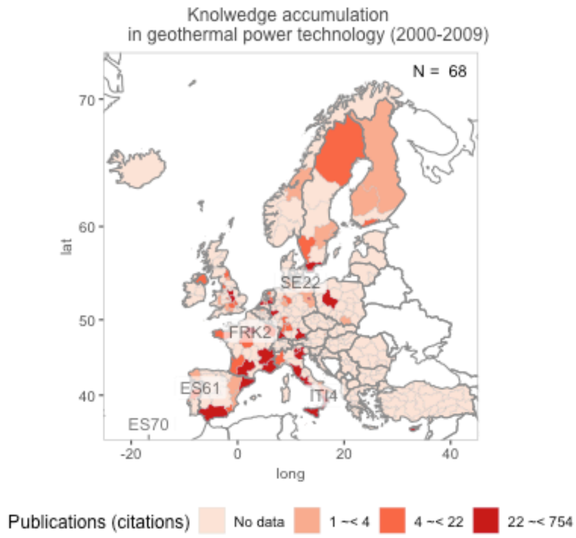


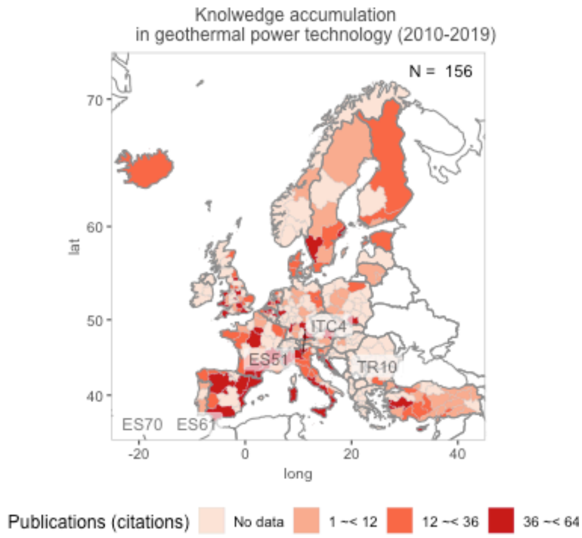
Share of electricity from ocean energy technology (average: 2010-2019)
Share
0.15
0.10
0.05
0.00
FR ES PT AL AT BE BG CY CZ DE DK EE EL FI HR HU IE IS IT LT LU LV MK MT NL NO PL RO RS SE SI SK TR UA UK XK
Country

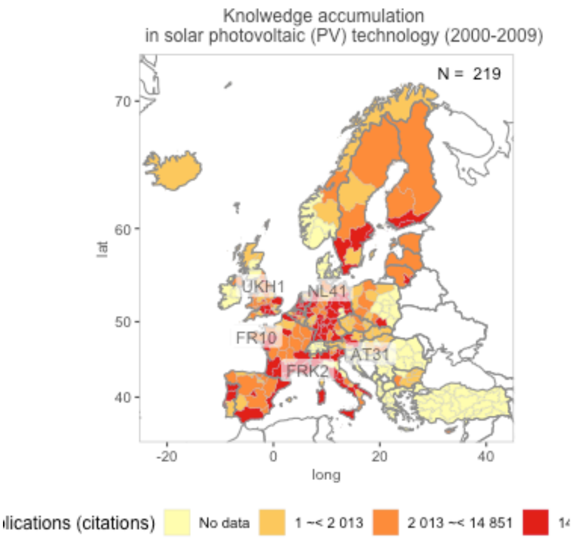
Appendix G. Knowledge accumulation

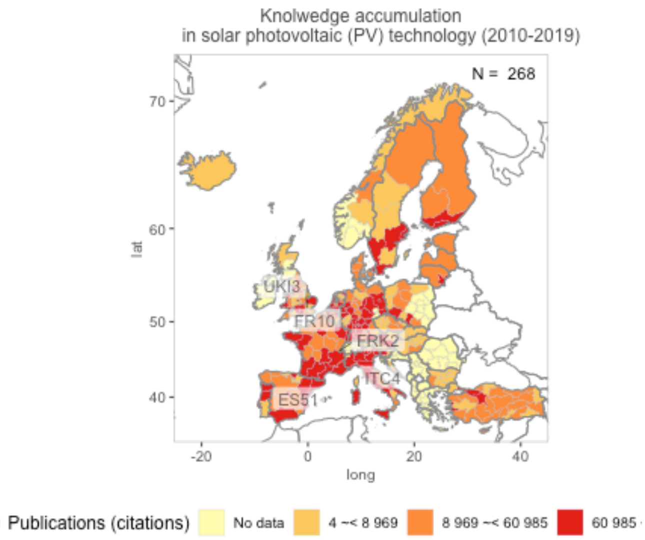


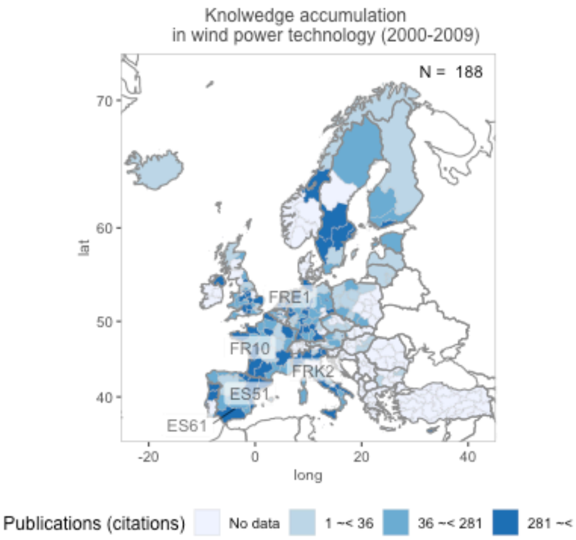








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FRK2
ES51
ES61
lat
long
Publications (citations)
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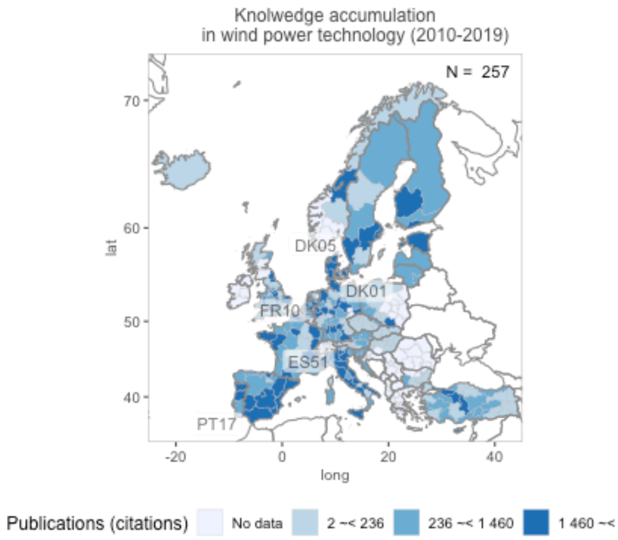
281 -<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in wind power technology (2010-2019)
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long
Publications (citations)
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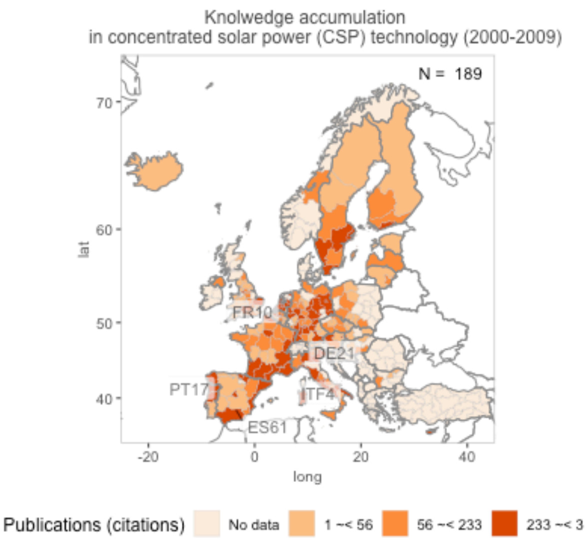
236 -< 1 460
1 460 -<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in concentrated solar power (CSP) technology (2000-2009)
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DE21
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lat
long
Publications (citations)
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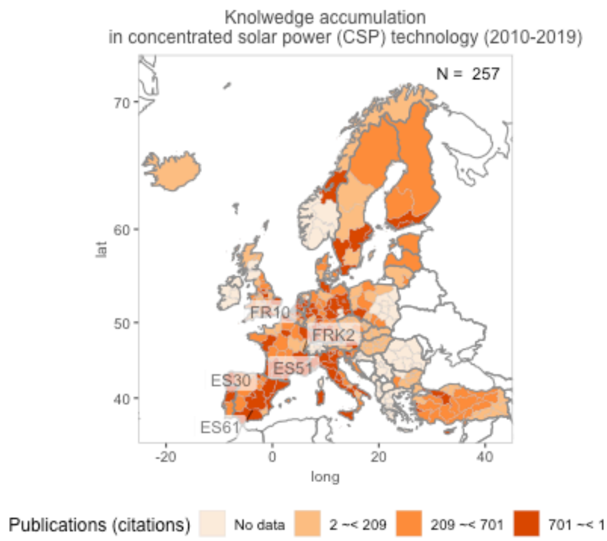
56 -< 233
233 -< 3


Knolwedge accumulation
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lat
long
Publications (citations)
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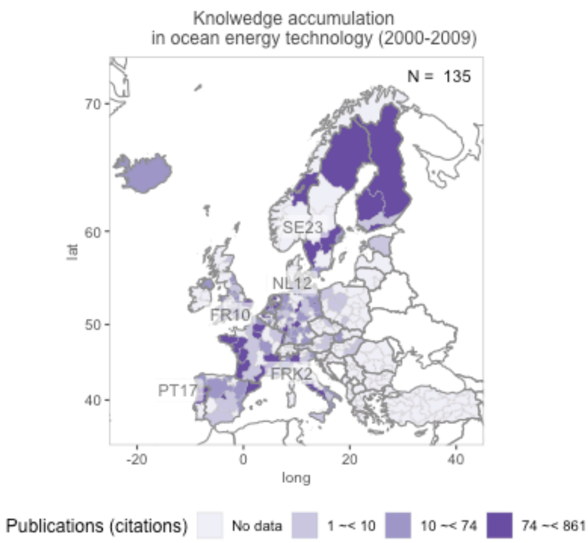
209 -< 701
701 -< 1


Knolwedge accumulation
in ocean energy technology (2000-2009)
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Publications (citations)
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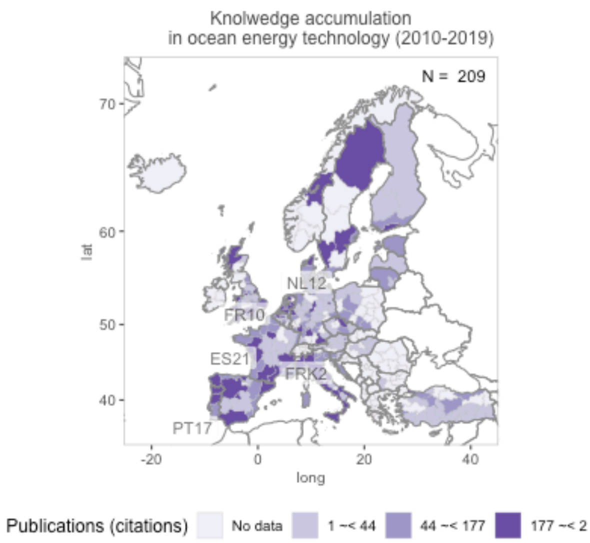
10 -< 74
74 -< 861


Knolwedge accumulation
in ocean energy technology (2010-2019)
N = 209
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FR10
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lat
long
Publications (citations)
No data
1 -< 44
44 -< 177
177 -< 2

Appendix H. Standard International Energy Product Classification (SIEC)

Based on the simplified energy balance

Main group	#	Energy fuel	Eurostat's database code
Fossil fuels	1	Solid fossil fuels	C0000X0350-0370
	2	Manufactured gases	C0350-0370
	3	Peat and peat products	P1000
	4	Oil shale and oil sands	S2000
	5	Oil and petroleum products (excluding biofuel portion)	O4000XBIO
	6	Natural gas	G3000
Renewables	7	Renewables and biofuels	RA000
Non-renewable waste	8	Non-renewables waste	C0000X0350-0370
Nuclear	9	Nuclear heat	N900H

Based on the complete energy balance for 'Renewables and biofuels' only

Main group	#	Energy fuel	Eurostat's database code
Renewables	7.1	Hydropower	RA100
	7.2	Geothermal	RA200
	7.3	Wind power	RA300
	7.4	Solar photovoltaic	RA420
	7.5	Solar thermal	RA410
	7.6	Tidal wave	RA500

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