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Not all peripheries are the same: The importance of relative regional innovativeness in transnational innovation networks

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Abstract

This paper aims to test the hypothesis according to which "relative" innovativeness (regions scoring higher than the national average in innovation rankings, such as the Regional Innovation Scoreboard) is more important than "absolute" innovativeness (regions scoring higher than the European Union [EU] average) in determining the centrality and key positioning of EU regions in highly selective and competitive international innovation networks. The combined adoption of various social network analysis techniques and econometric models in the specific arena of the EU nanotechnology network created within the Horizon 2020 program confirms this hypothesis. However, additional graph visualization and brokerage analysis highlight how such relative innovators, holding key positions in the targeted network, hardly act as gatekeepers in the respective national contexts. A major implication of this study is that although relatively innovative regions may play a key role in transnational innovation networks, their inadequate action as gatekeepers represents a negative aspect for peripheral regions in general and especially in marginally innovative countries. This finding raises doubts about the actual increasing and more effective knowledge circulation between the surveyed regions to which the EU explicitly aspires.

1 | INTRODUCTION

By implementing the European Research Area (ERA), the European Union (EU) aspires to create a single, borderless market for research and innovation by integrating scientific resources and the effective circulation of researchers, scientific knowledge, and technology across its member states (European Commission, 2020a). In this regard, the Framework Programs (FPs) periodically launched by the EU represent its most important innovation policy, which prioritizes strengthening the position of Europe in the global research and innovation arena. Among other things, the disparities observed between and within the various countries should be addressed by removing the barriers that impede access to knowledge sources and hinder related potential innovation outputs in peripheral EU areas. Thus, a balanced or, in any case, more even participation in FPs (European Parliament, 2018), primarily determined by a higher involvement of the less innovative or developed regions (Ukrainski et al., 2018), would be desirable and in line with the "harmonious development" promoted by the EU Cohesion Policy (European Commission, 2021).

The transnational innovation networks created within EU FPs are characterized by distinct core–periphery dynamics in which certain clearly identifiable organizations, generally located in the most innovative countries and regions, show a high degree of connectedness, hold key positions, form the network core, and foster a relatively stable web of relations (e.g., Balland et al., 2013; Hoekman et al., 2013; Roediger-Schluga & Barber, 2008; Wanzenböck et al., 2015). If these elements are confirmed, they would represent a clear and severe weakness of the preeminent EU innovation policy due to the previously mentioned necessity of enhancing the degree of participation of researchers and research groups operating in peripheral areas (European Parliament, 2018).

In contrast, the present paper questions the assertion that the most innovative regions, which are generally located in highly innovative countries, tend to hold key positions in EU innovation networks. More precisely, based on a thorough observation of the relational and geographical dynamics that have characterized the various EU programming cycles, I argue that being a highly innovative region per se (i.e., scoring above the EU average in innovation rankings, such as the regional innovation scoreboard [RIS]) is not automatically associated with more connections, strategic positioning, or the ability to join the core of EU innovation networks. What I intend to demonstrate is that being more innovative than the other regions of the same country (i.e., scoring above the national average in RIS) is a critical factor in determining the key positioning and coreness of a region. This hypothesis is backed by previous empirical analyses demonstrating how some marginally innovative regions at the EU level have been actually able to succeed in the various programming cycles (e.g., Calignano & Trippl, 2020; Scherngell & Barber, 2009). Moreover, marginally or moderately innovative countries seem to be characterized by an apparent association between regional innovativeness and degree of participation in the EU FPs, with the more developed regions undoubtedly playing a dominant role in the targeted national contexts (see, e.g., Calignano & Quarta, 2015, 2020). More generally, theoretical considerations and empirical evidence about innovation in noncore areas similarly provide a relevant backdrop for the present study (see, among many others, Eder & Trippl, 2019; Shearmur, 2012).

For practical reasons and to adopt clear and specific terminology, I define the regions that score higher than the EU average in RIS as "absolute" innovators and those that score higher than the respective national average in RIS as "relative" innovators. In other words, absolute innovators are considered as such in the specific geographical context under analysis (i.e., the EU) in the present study, thus representing the benchmark at the European level. In contrast, relative innovators refer to the most innovative regions in each national context. This definition, as well as the related approach, is flexible and can be adopted to different geographical scales, areas, and units of analysis.

In this study, a methodologic strategy comprising social network analysis (SNA) techniques, graph visualization, and econometrics (binary logistic and Tweedie models) was adopted to conduct empirical analysis in the context of the EU nanotechnology network created under the latest 7-year FP, named Horizon 2020 (hereafter H2020-NANOTECH). In particular, I used SNA measures, such as degree centrality (number of connections), betweenness centrality (strategic positioning), and the core–periphery model (coreness), to map the participation of EU regions in the targeted network and determine the possible association among these three dependent variables and two main independent variables: relative innovativeness and absolute innovativeness.

In addition, I used graph visualization and exploratory brokerage analysis (Borgatti & Everett, 2012) to reveal whether the regions that are mainly involved and strategically positioned in H2020-NANOTECH transfer the knowledge they acquire in transnational networks to the other regions of the same country. This analysis was based on two distinct but complementary types of brokers (i.e., gatekeepers and coordinators; Gould & Fernandez, 1989) and conducted by visualizing the relations established by the regions situated in five exemplifying countries (Sweden, the United Kingdom, Greece, Bulgaria, and Romania) characterized by different levels of innovativeness. Some considerations of the roles of gatekeepers (i.e., key nodes acquiring knowledge from participation in transnational networks) and coordinators (i.e., particular nodes enabling domestic knowledge circulation) were facilitated by extending the brokerage analysis to all surveyed EU countries and related regions (Appendix D—Table D1).

Based on these initial considerations, the following research questions are addressed in this paper: Is the level of regional innovativeness at the EU level (absolute innovativeness) or the national level (relative innovativeness) associated with the ability to hold key positions in H2020-NANOTECH? In particular, what are the main policy implications of such a possible association, especially for the peripheral EU regions located in marginally innovative countries?

The remainder of this paper is organized as follows. In Section 2, I reviewed the main literature on topics such as multiscalar and transnational innovation networks, EU programming cycles, and conceptualization of the "periphery" in geographical and economic terms, with the aim of framing the theoretical background of the present study. In Section 3, I provided a detailed description of the methodologic strategy used to conduct the empirical analysis. Finally, I presented the main results in Section 4, discussed them in Section 5, and reflected on the most important policy implications in Section 6, which also concludes the paper.

2 | LITERATURE REVIEW

2.1 | Growing importance of transnational innovation networks

Innovation is no longer driven by the episodic events associated with individuals; rather, it materializes systemically and involves various actors and social relations. For example, Walshok et al. (2014, p. 347) noted that "[w]hile organizations were once the center of innovation research [...] today geographic regions are often the platform for innovation studies," thus stressing the increasing importance of geography in shaping innovation dynamics at various geographical levels. In this respect, the economic geography literature now widely accepts that innovation occurs through social and relational processes in different systems and networks (e.g., Bathelt & Glückler, 2003, 2011; Powell & Grodal, 2005; Van Egeraat et al., 2014).

Although economic geographers have traditionally dealt with local knowledge exchange, recent research has stressed the increasing importance of multiscalar interactions for innovation. This means that innovation outcomes generally depend on how regional organizations coordinate their activities through webs of relations in different geographical areas. The implication for economic geographers is that knowledge exchange and related innovation processes should be examined by adopting a relational lens and a multiscalar perspective (Bathelt et al., 2004; Coe & Bunnel, 2003; Dicken & Malmberg, 2001).

In other words, organizations strongly benefit from being embedded in transnational innovation networks in which they can find complementary skills and competencies that are neither easily nor readily available within their regional or national boundaries. Consequently, as many scholars have observed, long-distance knowledge sources have become increasingly important in the last two decades, thus delineating new geography of knowledge flows (Maggioni & Uberti, 2011; Narula, 2002; Vale, 2011).

Although geographical proximity remains a critical factor in knowledge circulation between colocated organizations (e.g., Buzard et al., 2020; Caragliu & Nijkamp, 2016; Sonn & Storper, 2008), many scholars have demonstrated how long-distance connections might be even more important in triggering innovation outcomes, and that, in any case, they represent an extremely helpful complement to localized knowledge exchange (Chaminade et al., 2021; Fitjar & Rodríguez-Pose, 2011; Lagendijk & Lorentzen, 2007; Martin et al., 2018).

In this regard, "local buzz" (regional ties) engenders trust, reduces transaction and information costs, and creates localized knowledge spillovers (Audretsch & Feldman, 1996; Storper & Venables, 2004). In contrast, "global pipelines" (international connections) represent a remedy to possible cognitive and functional lock-ins (Martin & Sunley, 2006) and competency traps (Boschma, 2015), especially in highly specialized or less developed regions, due to the new ideas and creativity fostered by connections with partners located in distant locations. Similarly, other contributions have revealed that regional innovation can be determined by relevant long-distance knowledge flows, even in geographical areas that are characterized by weak innovative structures, sparse companies, lack of investments in research and development (R&D), and geographical marginality (Fitjar & Rodríguez-Pose, 2011; Grillitsch & Nilsson, 2015).

However, factors such as organizational and regional knowledge bases (Asheim & Gertler, 2005) and absorptive capacity (i.e., the ability to recognize, assimilate, and exploit relevant external knowledge; Cohen & Levinthal, 1990) influence the possibility of establishing fruitful relations with more distant partners (Badillo & Moreno, 2015; Martin & Moodysson, 2011; Plum & Hassink, 2014). For example, Aarstad et al. (2016) showed that international collaborations are most beneficial for innovation outcomes but only for larger enterprises with the necessary level of absorptive capacity to simultaneously manage regional and international collaborations. However, not all regions seem to be adequately equipped for this purpose (Fitjar & Rodríguez-Pose, 2015).

2.2 | Why FPs and why precisely the EU nanotechnology network?

Since the first programming cycle, launched during 1984–1988, the EU has adopted a collaborative approach to innovation policy by promoting multiscalar cooperation. In particular, the main objective of the programming cycles periodically implemented by the EU is to encourage the creation of research consortia, thereby enabling knowledge creation and circulation among various innovative actors (e.g., private companies, universities and research centers, public authorities, venture capitalists; Roediger-Schluga & Barber, 2008). Moreover, EU FPs represent a vital funding source for businesses and research establishments. This is true for all EU regions, but especially for those characterized by low R&D intensity, specialization in traditional sectors, geographical marginality, and a lack of knowledge circulation among their few co-located organizations (Schulze-Krogh & Calignano, 2020).

Many previous studies have examined the spatial and relational dynamics and effects of collaborative projects funded under various EU FPs. The intrinsic characteristics of EU FPs have motivated many scholars to adopt a network approach in their empirical analyses. As previously mentioned, these studies have highlighted a persistent core–periphery structure wherein the core is primarily represented by regional organizations situated in the most innovative, competitive, open, and technologically complex EU regions (Balland et al., 2013; Cecere & Corrocher, 2015; Muscio & Ciffolilli, 2018).

In other words, although even participation of countries and regions is an objective explicitly stated by the EU in various official documents (e.g., European Parliament, 2018), several research articles and evaluation reports have highlighted how such participation is highly skewed and biased toward the more innovative or developed member states and regional areas (e.g., Balland et al., 2013; Calignano & Quarta, 2015; European Commission, 2018; Roediger-Schluga & Barber, 2008). For example, the H2020 program is characterized by a remarkable uneven geographical representation. In particular, only German participants received 17% of the overall funding, whereas participants from five countries—the United Kingdom, Germany, France, Spain, and Italy—received 60% of the overall funding. Conversely, participants from Bulgaria, Latvia, and Lithuania (three Eastern European countries that joined the EU in correspondence to the relatively recent historic enlargement in 2004) received a very limited amount of funds, corresponding to 0.1% each (European Commission, 2018). Similarly, the funds allocated through FPs were heavily concentrated in more developed EU regions, with only a few less developed regions—generally located in countries that traditionally score moderately or particularly well in EU programming cycles (Greece and the United Kingdom)—showing a certain ability to acquire vital research funds (e.g., Schulze-Krogh & Calignano, 2020). These results represent a severe drawback in considering EU policy guidance for applicants and evaluators aiming to forge rather broader participation across different countries and regions (European Commission, 2018; European Parliament, 2018).

However, observing the networks created throughout the various FPs, I argue that a thorough analysis of how EU funds are allocated within each national context may lead to original results. In particular, I hypothesized that more innovative regions in weaker countries may perform analogously well and that the positioning in EU innovation networks is primarily determined by the role that regions play in their respective domestic contexts rather than their hierarchical positions in the EU as a whole. This possible factor was surprisingly not adequately tackled, and even neglected, in previous empirical analyses, despite the important consequences that it, if confirmed, may have in terms of policy implications and future guidance.

Based on these considerations, I conducted an empirical analysis in the specific context of the EU nanotechnology network. As mentioned above, I examined all joint projects with nanotechnology as their main topic, funded under the latest H2020 program (2014–2020 period). The aim was to test my hypothesis, according to which relative innovativeness is more important for a region than absolute innovativeness for holding a central, strategic, or core position in highly competitive transnational innovation networks.

The EU nanotechnology network seems to be an ideal arena for conducting the present empirical analysis. There are at least four reasons for this. First, the EU includes nanotechnology among the so-called key enabling technologies that can enable countries and regions to successfully tackle severe societal challenges, such as environmental issues, ageing population, optimization of resource use, and development of digital technologies. Hence, by analyzing the H2020-NANOTECH program, I could capture the spatial and relational dynamics of an irruptive and critical field for each EU regional area, as emphasized by the EU itself (Calignano & Quarta, 2015). Second, the interdisciplinary nature of nanotechnology enables researchers to study knowledge exchange dynamics, potential innovation outcomes, and possibly development trajectories from a global perspective—that is, by adopting a multiscalar approach and considering all traditional and high-technology sectors and industries in which nanotechnology can be applied (e.g., food, ceramics, textiles, building, biotechnology, and information and communication technology; Calignano & Quarta, 2015). Third, knowledge exchange in the nanotechnology field mainly occurs in transnational innovation systems and networks, wherein temporary, social, and technological proximities are more important than mere geographical proximity (Calignano, 2014). Fourth, multiscalar interactions and transcalar cooperation are incentivized by the analytic knowledge base that characterizes the nanotechnology field (Asheim & Gertler, 2005). In other words, nanotechnology is a science-based industry in which knowledge is generally exchanged through codified channels, such as patents and scientific publications (Guilhon, 2017). This makes exchanges with more distant partners possible and relatively easier than those in industries primarily characterized by the tacit knowledge content in which face-to-face contact seems to be dominant (i.e., synthetic/engineering-based and symbolic/creativity-based knowledge bases; Asheim & Gertler, 2005).

These four elements make the nanotechnology projects funded under the H2020 program an excellent database for conducting a reliable multiscalar analysis and providing interesting considerations and policy reflections on the relation between positioning in EU innovation networks and relative and absolute innovativeness.

2.3 | Concept of "periphery" and how it is operationalized in this paper

As previously mentioned, regions are diverse, and their characteristics may contribute to determining their degree of participation in innovation networks at various geographical levels. In the geography and cognate literature, concepts such as "core" and "periphery" are traditionally and largely used, even though there is no unanimous agreement on their definition.

In geographical and economic terms, "core regions" refer to prosperous and dominant economies characterized by geographical centrality and high population density (Azaryahu, 2008). Conversely, the concept of "periphery" is much more contested and can be outlined by adopting three different perspectives: anthropological, sociological, and geographical (Pezzi & Urso, 2017).

If the anthropological approach sees peripheral areas in terms of asymmetric power or hierarchical subordination to dominant cores, the two other perspectives provide more helpful insights into how "peripheries" are conceptualized in this paper. In fact, the sociological approach adds new relevant elements to the discussion—for example, the existence of a "semi-periphery" and the fact that it can be hypothesized as a continuum between the two endpoints (i.e., the core and periphery). The geographical perspective is even more interesting for the purposes of the present empirical analysis. According to this approach, peripheral areas share some characteristics (geographical distance to core areas, weak economies, and outmigration); however, the relativity of the "peripherality" concept must be emphasized because, according to Hall et al. (2013, p. 72), "where the periphery is depends on where you stand" (see Pezzi & Urso, 2017, for a detailed examination of the three approaches to the concept of "periphery").

The intrinsic "relativization" in Hall et al.'s (2013) definition perfectly coincides with the way peripheral areas are conceptualized and operationalized in this paper. For example, a region can be peripheral in absolute terms (compared to the other EU regions in our case study) but plays a predominant role in its specific national context (what I define as relative innovativeness). These considerations are further supported by Walshok et al. (2014, p. 348), who argued that although transnational networks connect places selectively and core regions have clear advantages in this regard, "[e]very country has its major node(s) that connect(s) the country to strategic global networks [the relative innovators in the present case study; author's note]. These nodes underlie the formation of metropolitan regions that determine the local/global spatial structure of each country through their internal, multilayered networking."

3 | METHODOLOGICAL STRATEGY

I adopted SNA techniques, graph visualization, and regression analysis (binary logistic and Tweedie models) to test the existence of a relation between the level of innovativeness at the EU and the national levels of a given region and the ability of such a region to play a central role (degree), hold a key position (betweenness), and join the core (core–periphery model) of the EU innovation networks. In particular, I hypothesized that relative innovativeness is a key factor in this respect and is even more important than being a highly innovative region per se (absolute innovativeness).

As mentioned before, my empirical analysis was conducted in the context of the EU nanotechnology network. I collected data on 853 collaborative projects that were funded by H2020-NANOTECH (i.e., the 2014–2020 period). In particular, I used all projects tagged as "nanotechnology" and "nanoscience(s)" on the Community Research and Development Information Service website to map the collaborations established by the organizations located in 221 EU regions (Nomenclature of Units for Territorial Statistics [NUTS] 0, NUTS 1, and NUTS 2 levels).[1]

Using this relational data set, I could conduct SNA and calculate the three dependent variables that I employed in the proposed econometric analysis (degree, betweenness, and core–periphery). I used other databases (i.e., RIS; European Quality of Government Index [EQI], Academic Ranking of World Universities [ARWU], and Eurostat] to build the independent and control variables (see Section 3.2 and Appendix A—Table A1 for details).

3.1 | Network analysis and dependent variables in econometric models

I used a case-by-case matrix in which the EU regions (NUTS 0, NUTS 1, and NUTS 2 levels) represent the cases for mapping the ties among the regional organizations that participated in H2020-NANOTECH. Two regions are considered connected when their respective organizations participate in at least one joint research project. In this regard, although individuals and organizations mostly represent the cases in which network analyses are conducted in the various disciplines forming social sciences, the increasing interest of economic geographers and regional scientists in the relational dimension of innovation activities has motivated them to use cities, regions, or even countries as the units of analysis. For example, Tóth et al. (2020) used SNA to demonstrate the existing link between the economic network structures of the EU regions and their resilience to economic shocks, and Balland and Boschma (2021) showed how interregional linkages among the various EU regions determine a positive effect in terms of regional diversification. In addition, Balland et al. (2019) and Calignano (2021) applied various SNA measures, such as degree, betweenness, eigenvector, and structural holes, to assess the network dynamics in the H2020 program by using countries and regions as units of analysis in their reconstructed case-by-case matrices.

In this study, I used several SNA measures (such as density, average degree, and centralization) to provide an overview of the network structure. In addition, I used two centrality measures—degree and betweenness—and the core–periphery model to determine the dependent variables of my econometric models.

- Degree centrality refers to the total number of ties that a region established in H2020-NANOTECH; in the case of degree, the regions showing the maximum ties are considered the most important and “central” ones (Scott, 2000).
- Betweenness centrality refers to the probability that a region lies on paths between other regions; this means that regions with higher betweenness can manage knowledge diffusion in the targeted network. In other words, a high level of betweenness makes certain regions particularly influential, as their domestic organizations can “control” the relevant information exchanged in a given network by managing and filtering the knowledge acquired from other regions. In this way, they may act as either structural bridges (nodes connecting one part of a graph to another) or, conversely, hinder the knowledge transfer between disconnected regions (Balland et al., 2013; Calignano, 2021; Calignano & Trippl, 2020). Moreover, these regions may hold a particularly advantageous position through which they can benefit from different interregional knowledge flows, enabling the compensation for the missing technological capabilities (Balland et al., 2013; Tóth et al., 2020). Of similar importance is the fact that the removal of a region characterized by high betweenness from a network can create disruptions because of its strategic positioning. This latter element, together with the “bridging” role played by the regions that score high in terms of betweenness (Balland et al., 2013), is similar to the concept of brokerage (Borgatti & Everett, 2012). I used this SNA measure combined with graph visualization to provide some considerations of knowledge acquisition and circulation that are potentially triggered by key regions acting as brokers (particularly, gatekeepers and coordinators; Gould & Fernandez, 1989; see Section 4.3 for a further explanation of how graph visualization and brokerage analysis are used in this paper).
- The core–periphery model intuitively refers to a core–periphery structure within which some regions are better connected than others. In other words, there are “two classes of nodes,

namely a cohesive subgraph (the core) in which actors are connected to each other in some maximal sense and a class of actors that are more loosely connected to the cohesive subgraph but lack any maximal cohesion with the core (i.e., the periphery; author's note)" (Borgatti & Everett, 1999, p. 377).

The characteristics of degree and betweenness (i.e., noninteger normalized variables, point mass distribution at zero, and exponential distribution) led me to apply the Tweedie model. Conversely, I employed binary logistic regression when I adopted the core–periphery model as the dependent variable (above EU/above the national average = 1; below EU/below national level = 0).

3.2 | Independent and control variables

I used the average performance score of each EU region in RIS, with specific regard to the editions from 2014 to 2019 (hereafter RIS2014-2019), as a proxy of regional innovativeness.[2] This period was chosen based on the years in which the various editions of RIS were issued and by considering the beginning (2014) and the year before the end (2019) of the latest EU programming cycle (i.e., H2020 implemented during 2014–2020).

In particular, I built two main independent variables based on the average score of each region in RIS2014–2019. These variables correspond to absolute innovativeness (i.e., overall average RIS2014–2019 performance score: 1 = above EU average, 0 = below EU average) and relative innovativeness (i.e., the score of an EU region compared to the other regions of the same country: 1 = above the national average, 0 = below the national average).

Finally, I used control variables, such as regional population, gross domestic product (GDP) per capita, quality of institutions, and scientific excellence, to validate the proposed econometric models.

The size of regions, measured through the regional population, may influence the degree of participation, ability to play a strategic role, and coreness in EU FPs (e.g., Calignano & Trippl, 2020). Similarly, scientific excellence may represent a critical factor in determining the ability to join the network core and play a key role in EU innovation networks (on the relation between scientific excellence or productivity and participation in international research and innovation programs, see Enger & Castellacci, 2016). In particular, scientific excellence was proxied by a categorical variable based on the number of times a university situated in a given region appeared in the specific ranking of ARWU devoted to "nanoscience and nanotechnology" (hereafter ARWU–nanotechnology). The pertinence of this variable was demonstrated by previous studies conducted in H2020-NANOTECH that considered different units of analysis (Calignano & Trippl, 2020), and from a more theoretical perspective, considering the intrinsic characteristics of nanotechnology—that is, a science-based field in which knowledge exchange is primarily codified and which sees the frequent engagement of universities and other research organizations (Asheim & Gertler, 2005; Guilhon, 2017). Finally, the quality of a regional government is indicated by EQI—that is, the survey data allowing researchers to measure how governance varies between different EU regions and within each country. This institutional variable must be considered given its widely documented importance in enhancing economic development (e.g., Rodríguez-Pose & Di Cataldo, 2015; Rodríguez-Pose & Garcilazo, 2015), although a recent analysis conducted in another research program funded by H2020—namely, the "Energy" program—has shown the limited impact of good governance on the determination of network centrality or key positioning (Calignano & Trippl, 2020).

Finally, I validated all employed econometric models, with the aim of testing their robustness against alternative models. In particular, I replaced regional population with population density (inhabitants/km^2) and used different metrics for the quality of regional institutions (binary variables instead of continuous variables: 1 = above EU or national average, 0 = below EU or national average, depending on the main independent variable) and scientific excellence (binary variables instead of categorical variables: 1 = presence of regional universities in ARWU–nanotechnology; 0 = absence of regional universities in ARWU–nanotechnology). All variables employed in the main econometric models and related robustness checks are described in detail in Appendix A–Table A1.

4 | EMPIRICAL ANALYSIS

4.1 | Characteristics of the H2020-NANOTECH network and core–periphery dynamics

Initially, I calculated certain network statistics to reveal the main characteristics of the network under analysis. On average, each EU region established connections with 62 counterparts, while the median degree is not dissimilar and correspond to 60 connections. More interestingly, the H2020-NANOTECH program is characterized by a moderate degree of centralization (44%), which means that knowledge exchange does not exclusively involve a few regions, but rather is relatively widespread and balanced between the regions that form the targeted network.

Despite the high number of zeros in the network matrix (33 completely disconnected regions corresponding to more than 15% of the total), the overall density of H2020-NANOTECH is significantly higher than that in most of the previously examined networks in the same context (i.e., 13,670 ties, which correspond to 28% of the connected regions (see Table 1); for a comparison with the other innovation networks created within EU FPs, see, e.g., Calignano & Trippl, 2020; Calvo-Gallardo et al., 2021). This leads to the consideration of the existence of a distinct core–periphery structure (correlation fit = .89), in which, if we exclude the disconnected regions, the remaining participating regions will show a high degree of connectivity. Conversely, a lower degree of centralization is primarily materialized in a relatively balanced number of regions that form the core (89 regions; 40.3% of the total) and periphery (132 regions; 59.7% of the total) of the H2020-NANOTECH network. In particular, most of the disconnected regions are situated in the Eastern countries belonging to the so-called EU-13 (i.e., the countries that joined the EU in correspondence to its largest expansion, which occurred in 2004). Eighteen of the 33 regions are located in underrepresented Bulgaria, Czechia, Hungary, Poland, Romania, and Slovakia, whereas the remaining disconnected regions are very small or geographically remote regions situated in countries scoring higher in the various EU FPs, such as Germany, Greece, Spain, Italy, the Netherlands, Portugal, and Finland.

Other interesting elements are highlighted by network statistics and graph visualization. For example, the number of densely connected regions is higher than the number generally

TABLE 1 Network statistics: density, number of ties, average degree, median degree, and centralization

Density	Ties	Average degree	Median degree	Centralization
0.28	13,67	61.86	60.00	0.44

observed in other thematic FPs (e.g., Calvo-Gallardo et al., 2021), while the proportions of regions scoring above and below the EU average in RIS2014–2019 (i.e., absolute innovativeness) that form the network core is well balanced and quite evenly distributed. This latter aspect can be clearly observed in Figure 1, where the color of the circles represents the overall performance score in RIS2014-2019 (above EU average = green circles; below EU average = blue circles), while the bigger and more central circles represent the regions that form the network core.

The situation differs when we look at the relation between relative innovativeness and belonging to the network core. The graph in Figure 2 shows that the network core (the bigger and more central circles) comprises most of the regions that score above the national average (red circles). Therefore, the comparison between the graphs in Figures 1 and 2 preliminarily reveals that relative innovativeness is a key factor in determining the ability to join the H2020-NANOTECH core, and that it is potentially more important than absolute innovativeness, as hypothesized in the introductory section of the present paper.

4.2 | Econometric analysis: Absolute innovativeness, relative innovativeness, and key positioning in H2020-NANOTECH

I strengthened the abovementioned SNA results through a further econometric analysis, which confirms how relative innovativeness is clearly associated with the ability to join the H2020-NANOTECH network core (see Model 2 in Table 3), while the relationship between absolute innovativeness and coreness can be hardly observed (see Model 1 in Table 2).

In particular, Model 1 shows the existence of a positive but not statistically significant correlation between absolute innovativeness and holding a core position in the H2020-NANOTECH network. However, control variables, such as regional population, GDP per capita, and scientific excellence in the field of nanotechnology, are similarly positively correlated, although they are statistically significant in this case. Moreover, a higher quality of regional institutions is negatively correlated with core positioning, although such a relation is not statistically significant.

Model 2 confirms the SNA results presented above, which reveal a higher number of relative innovators than that of absolute innovators in the network core. The coefficients reported in Table 3 show a positive and statistically significant association between scoring above the

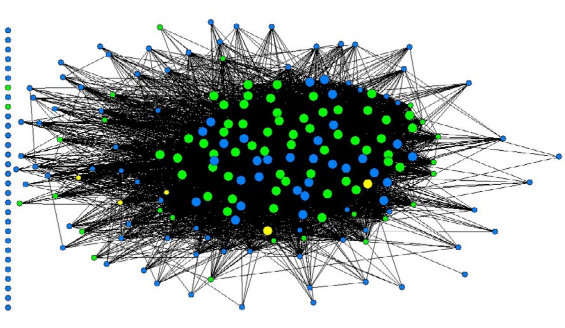

FIGURE 1 Structure of the H2020-NANOTECH network and identification of the network core. Green circles: regions scoring above the EU average in RIS2014–2019; blue circles: regions scoring below the EU average in RIS2014–2019; yellow circles: countries (NUTS 0) not included in the econometric analysis; bigger circles: core regions

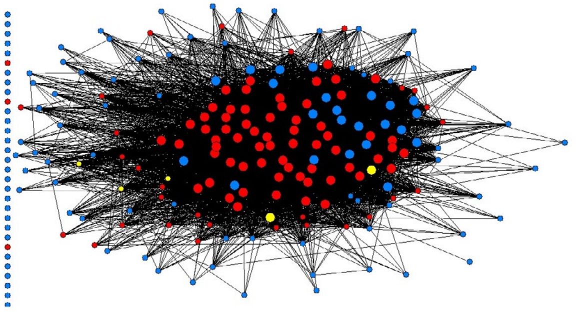

FIGURE 2 Structure of the H2020–NANOTECH network and identification of the network core. Legend – red circles: regions scoring above the national average in the RIS2014–2019; blue circles: regions scoring below the national average in the RIS2014–2019; yellow circles: countries (NUTS 0) not included in the econometric analysis; bigger circles: core regions

national average and being positioned in the H2020-NANOTECH core. In particular, a relative innovator is approximately three times more likely to join the core of the targeted EU innovation network than a region that scores below the national average (odds ratio: 3.11; 95% confidence intervals: 1.28–7.60). All control variables included in the econometric model show a positive and statistically significant association with the dependent variables (regional population, GDP per capita, and scientific excellence), with the only exception being the quality of regional institutions (i.e., a similarly positive but not statistically significant relation).

Having determined the existence of a positive relationship between relative innovativeness and holding a core position, I added a new dimension of analysis by testing the possible association between relative and absolute innovativeness and other critical SNA measures, such as degree and betweenness.

The results of Models 3–6, displayed in Table 4, strengthen the importance of relative innovativeness in determining key positioning; in contrast, there is no clear association between absolute innovativeness and both network centrality and strategic positioning in the H2020-NANOTECH program.

In particular, the application of the Tweedie model confirms that scoring above the national average is a determinant factor in the ability of a region to establish numerous ties and lie between the other EU regions. In addition, Models 4 and 6 confirm the results of the binary logistic regression conducted above (see Model 2 in Table 3), with regional population and GDP per capita associated with degree and betweenness. The main difference, in this case, is represented by scientific excellence, which is negatively (Model 4) or positively (Model 6) correlated with the dependent variables but, in any case, it is not statistically significant. Finally, the quality of the institutions is negatively correlated with both dependent variables but is not statistically significant (see Table 4 for details).

The results of Models 3 and 5, as well as the previously examined core–periphery model, reiterate that absolute innovativeness, although positively associated with degree and betweenness, is not statistically significant (Table 4). Moreover, the coefficients of the various control variables agree with the results of Models 4 and 6, in which relative innovativeness represents the independent variable. The main difference is that scientific excellence is positively correlated with degree centrality and is statistically significant in Model 5.

In addition, I conducted one robustness test for each econometric model applied (see Section 3.2 and Appendix A—Table A1 for details about the newly independent and control

TABLE 2 Binary logistic regression. Dependent variable: core–periphery model

	Model 1	95% CI Lower	95% CI Upper
Absolute innovativeness	1.23 (0.71) 3.41	0.85	13.75
Population$_{log}$	2.00* (0.79) 7.45	1.59	34.94
GDP per capita	1.01** (0.27) 2.74	1.61	4.67
Quality of institutions	−0.61 (0.38) 0.54	0.26	1.13
Scientific excellence	1.61** (0.39) 5.02	2.32	10.83
Constant	−11.16** (2.77)		
Hosmer–Lemeshow test	6.05		
Pseudo R^2	.47		
Observations	216		

Note: Standard errors are in parentheses; odds ratios below the standard errors.
**Statistically significant at the .01 level; *statistically significant at the .05 level.

variables employed). In summary, the various robustness checks confirm the lack of correlation between absolute innovativeness and holding a key position in H2020-NANOTECH, while they again show the existence of an association between relative innovativeness and being positioned in the core (core–periphery model; binary logistic regression) or holding a central and strategic position (degree and betweenness; Tweedie model) in H2020-NANOTECH (see Appendix C—Tables C1–C3).

4.3 | Graph visualization and brokerage analysis

The results of the SNA and econometric analyses conducted in this study highlight certain interesting network dynamics, which are graphically illustrated in Figure 3. To exemplify how knowledge exchange occurs in the H2020-NANOTECH program, I used part of the network under analysis, referring to five different targeted countries characterized by different levels of innovativeness (from innovation leader to modest innovator, according to the European Innovation Scoreboard 2020 [EIS2020]) and connectedness. The results of this analysis indicate

TABLE 3 Binary logistic regression. Dependent variable: core–periphery model

	Model 2	95% CI Lower	95% CI Upper
Relative innovativeness	1.13*	1.28	7.59
	(0.45)		
	3.11		
$Population_{log}$	2.03**	1.56	37.44
	(0.81)		
	7.65		
GDP per capita	0.81**	1.26	3.96
	(0.29)		
	2.24		
Quality of institutions	0.35	0.60	1.78
	(0.27)		
	1.04		
Scientific excellence	1.58**	2.21	10.75
	(0.40)		
	0.40		
Constant	−10.69**		
	(2.88)		
Hosmer–Lemeshow test	9.34		
Pseudo R^2	.48		
No. of EU regions	216		

Note: Standard errors are in parentheses; odds ratios below the standard errors.

**Statistically significant at the .01 level; *statistically significant at the .05 level.

that considerable differences exist between regions and countries characterized by a diverse level of innovativeness, especially between relative innovators and the other domestic peripheral regions situated in marginally innovative countries.

Although further and more in-depth investigations are required, the combination of graph visualization and brokerage analysis presented in this section indicates that "not all peripheries are the same." In other words, the possibility of playing a key role or joining the core of competitive transnational innovation networks for a region situated in countries classified as moderate or modest innovators in EIS2020 may be particularly affected by relative innovativeness, especially if these countries are characterized by significant regional inequalities (e.g., Calignano & Quarta, 2015).

In my illustrative graph, the circles and diamond-shaped nodes indicate regions situated in Sweden (innovation leader, orange nodes), the United Kingdom (strong innovator, blue nodes), Greece (moderate innovator, green nodes), Bulgaria (modest innovator, red nodes), and Romania (modest innovator, yellow nodes), whereas the lines show the ties established within each country and between the five different targeted countries (in the latter case, the thickness of the lines reflects the strength of the relation between the respective regions).

TABLE 4 Tweedie model with country fixed effects (reference country: Belgium). Dependent variables: degree (Models 3 and 4) and between (Models 5 and 6)

	Model 3 Degree	Model 4 Degree	Model 5 Between	Model 6 Between
Absolute innovativeness	0.43		0.38	
	(0.26)		(0.43)	
Relative innovativeness		0.66**		0.92**
		(0.15)		(0.22)
Population density$_{log}$	1.40**	1.22**	2.70**	2.45**
	(0.25)	(0.25)	(0.39)	(0.39)
GDP per capita	0.33**	0.20**	0.62**	0.47**
	(0.07)	(0.07)	(0.09)	(0.96)
Quality of institutions	0.11	−0.40	0.26	−0.33
	(0.44)	(0.44)	(0.63)	(0.63)
Scientific excellence	0.02	−0.02	0.25*	0.17
	(0.09)	(0.09)	(0.12)	(0.12)
Country fixed effects	Yes	Yes	Yes	Yes
Constant	−7.24**	−5.81**	−12.92**	−11.41**
	(0.95)	(0.94)	(1.40)	(1.38)
Likelihood χ^2	142.71**	159.67**	251.84**	268.26**
No. of EU regions	216	216	216	216

Note: Standard errors are in parentheses.

**Statistically significant at the .01 level; *statistically significant at the .05 level.

As the graph intuitively suggests, the level of innovativeness clearly overlaps with the degree of connectedness in H2020-NANOTECH. After reporting that most of the regions in Sweden and, especially, in the United Kingdom, are connected with each other and with many other regions situated in other countries, it is worth noting that Greece is characterized by a moderate internal and external degree of connectedness, while Romania and Bulgaria are very weakly connected. Moreover, in these three latter countries, relative innovativeness (highlighted by bigger circles in Figure 3) is the determinant of the ability of a region to join the network core (see the diamond-shaped nodes) or, in any case, to establish more connections (degree) than the other regions of the same countries.

An important aspect that needs to be briefly examined is that the few regions in Romania and Bulgaria that can connect with strongly embedded regions in other countries do not act as brokers in their respective national contexts. A broker is a key node that significantly contributes to network integrity and viability (Long et al., 2013) and, if operating effectively, can facilitate the transfer of knowledge to disconnected regions (i.e., primarily peripheral regions in the respective national context, in my targeted network). Gould and Fernandez (1989) differentiated between broker types depending on their actual connecting role (Figure 4). For the purposes of the present study, I am particularly interested in the role of "gatekeepers" (Region A belongs to one country, and Regions B [broker] and C belong to another country) and "coordinators" (Nodes A, B [broker], and C belong to the same country), as they may diffuse the knowledge acquired elsewhere (gatekeepers) or help it circulate within their national borders (coordinators).

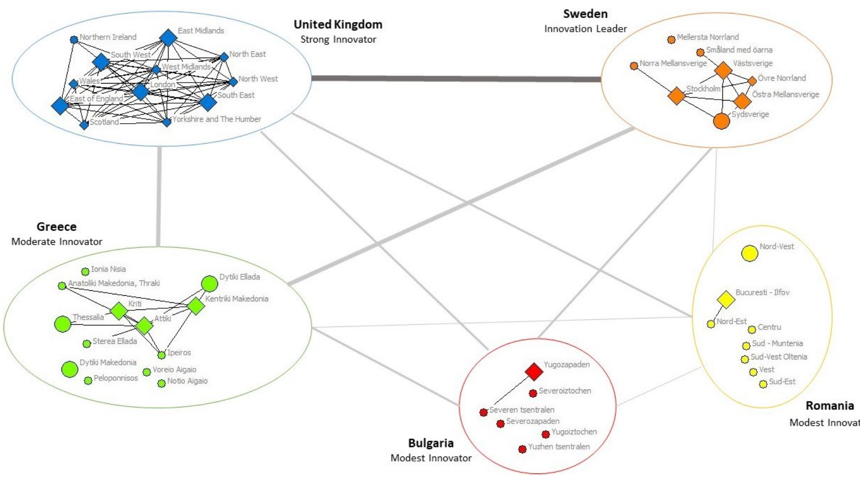

FIGURE 3 Graphical visualization (part of the H2020-NANOTECH network). Targeted countries: Sweden (orange nodes—innovation leader), United Kingdom (blue nodes—strong innovator), Greece (green nodes—moderate innovator), Bulgaria (red nodes—modest innovator), and Romania (yellow nodes—modest innovator). Diamond-shaped nodes: core regions; bigger nodes: relative innovators

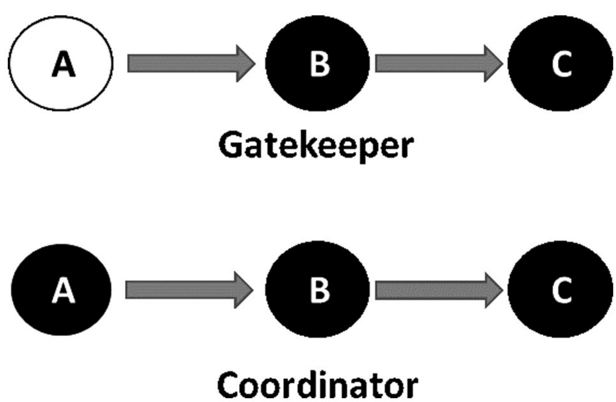

FIGURE 4 Brokerage roles: Gatekeepers and coordinators (Borgatti & Everett, 2012; Gould & Fernandez, 1989)

Figure 3 explicitly shows that the regions I defined as relatively innovative in countries classified as "modest" innovators (primarily Bucuresti-Ilfov in Romania and Yugozapaden in Bulgaria) do not trigger domestic knowledge circulation in the respective national contexts and remain disconnected from the other regions situated in the same country. These latter regions, in turn, cannot act as coordinators (i.e., brokers within the national context, which enable the circulation of knowledge acquired outside the country) because they do not benefit at all from the knowledge that the gatekeepers acquired in the H2020-NANOTECH program.

The situation is different in the moderately innovative Greece, where the gatekeepers (5 out of 13 regions) and coordinators (3 out of 13 regions) identified through the brokerage analysis acquire external knowledge through their participation in transnational networks (gatekeepers) and enable moderate circulation within the national borders, which, in any case, primarily involves the gatekeepers themselves (Figure 3). Moreover, the scores of the various gatekeepers are not evenly distributed and are accompanied by the sharp predominance of Attiki (where the capital Athens is situated) over the other Greek regions.

A strong innovator, such as the United Kingdom, represents the ideal scenario for the occurrence of knowledge diffusion, with all domestic regions acting as gatekeepers and showing much more balanced brokerage scores than the other targeted countries that are used as examples in this paper (Table 5). Finally, a leading innovator, such as Sweden, is characterized by a good degree of internal connectedness, a single disconnected region (the marginally innovative Mellersta Norrland), and three relatively innovative regions that act as the main gatekeepers and sole coordinators (Stockholm, Östra Mellansverige, and Västsverige).

The brokerage scores of all regions situated in all EU countries, which largely validate the observation in the part of the network illustrated in Figure 3, are listed in Appendix D—Table D1.

5 | DISCUSSION OF THE MAIN RESULTS

Based on the observations of previous empirical analyses conducted in the context of EU FPs (e.g., Balland et al., 2013; Cecere & Corrocher, 2015; Muscio & Ciffolilli, 2018), this paper questions whether a high level of innovativeness per se (absolute innovativeness) is a key factor in holding central, strategic, or core positions in highly competitive transnational innovation networks, such as EU FPs. This reflection motivated me to validate the hypothesis that relative innovativeness (i.e., scoring above the national average in innovation rankings, e.g., RIS 2014–2019 in the present empirical analysis) is crucial in determining optimal positioning in H2020-NANOTECH—that is, the innovation network I specifically examined in this paper. The validation of this hypothesis primarily affects regions in marginally innovative countries, in which relative innovators can join the network core or hold a key position, while all other regions risk remaining excluded from the vital knowledge flows engendered by EU FPs.

Consequently, based on the results of my empirical analysis, I confirm that not all "peripheries" are the same. Irrespective of the level of innovativeness of the country in which the targeted regions are situated, the relative dimension of "peripherality" (Hall et al., 2013; Pezzi & Urso, 2017) plays a key role in determining the degree of participation or node positioning in the EU nanotechnology network, although it seems to have a stronger impact on marginally innovative countries, as I illustrated before in the empirical part of this paper and will discuss in greater depth hereafter.

In general, the network under analysis is characterized by a higher density compared to other networks that were previously examined in analogous contexts (e.g., Calignano & Trippl, 2020; Calvo-Gallardo et al., 2021). Although more EU regions are involved in knowledge exchange dynamics, a result that contributes to determining a lower network centralization, the degree of participation remains uneven, with a clearly identified core–periphery structure. This result is not dissimilar to what many scholars have argued. What primarily differentiates this study from the previous ones conducted in the same arena is the fact that it demonstrates that being an innovative region in absolute terms is not clearly associated with holding a key position in the surveyed innovation network (regarding the fact that the more innovative regions participate more often or hold key positions in EU FPs, see, e.g., Balland et al., 2013; Calignano & Hassink, 2016; Hoekman et al., 2013). Despite the positive sign of the coefficients, the relation between absolute innovativeness, on one hand, and degree, betweenness, and coreness, on the other hand, is not statistically significant in the models applied. Conversely, as rightly hypothesized, all

TABLE 5 Brokerage scores: gatekeepers and coordinators. Targeted countries: Sweden, United Kingdom, Greece, Bulgaria, and Romania

Country	EIS2020	Region	Gatek.	Coord.
Bulgaria	Modest	Severozapaden	0	0
		Severen Tsentralen	0	0
		Severoiztochen	0	0
		Yugoiztochen	0	0
		Yugozapaden	117	0
		Yuzhen Tsentralen	0	0
Greece	Moderate	Anatoliki Makedonia, Thraki	0	0
		Kentriki Makedonia	130	2
		Dytiki Makedonia	0	0
		Ipeiros	35	2
		Thessalia	0	0
		Ionia Nisia	0	0
		Dytiki Ellada	17	0
		Sterea Ellada	0	0
		Peloponnisos	0	0
		Attiki	571	32
		Voreio Aigaio	0	0
		Notio Aigaio	0	0
		Kriti	92	6
Romania	Modest	Nord-Vest	0	0
		Centru	0	0
		Nord-Est	2	0
		Sud-Est	0	0
		Sud-Muntenia	0	0
		Bucuresti-Ilfov	84	0
		Sud-Vest Oltenia	0	0
		Vest	0	0
Sweden	Leader	Stockholm	218	10
		Östra Mellansverige	133	2
		Småland med öarna	0	0
		Sydsverige	19	0
		Västsverige	241	10
		Norra Mellansverige	1	0
		Mellersta Norrland	0	0
		Övre Norrland	10	0

TABLE 5 (Continued)

Country	EIS2020	Region	Gatek.	Coord.
United Kingdom	Strong	North East	65	0
		North West	97	0
		Yorkshire and The Humber	152	0
		East Midlands	106	0
		West Midlands	265	16
		East of England	313	16
		London	360	16
		South East	237	0
		South West	227	0
		Wales	123	0
		Scotland	218	0
		Northern Ireland	2	0

econometric models I carried out suggest the existence of a positive and statistically significant correlation between relative innovativeness and central or key network positioning.

The first aspect that deserves to be highlighted again is that the regions situated in less innovative countries primarily benefit from being relative innovators. In other words, whether it is, in a certain sense, predictable that more innovative regions in more innovative countries hold key or core positions (e.g., Balland et al., 2013; Calignano & Hassink, 2016; Hoekman et al., 2013), regions scoring above average in marginally innovative countries are not expected to achieve similar results, which is evidently due to their lower level of innovativeness in absolute terms.

It cannot be denied that this result might depend on the positive attitude of EU evaluators toward fostering diversified participation, which involves more balanced knowledge flows between strongly innovative areas and more peripheral regions (often situated in marginally innovative countries). In this regard, the necessity of promoting the inclusion of deprived regional areas has already been highlighted in various academic papers and technical reports (e.g., Calignano & Trippl, 2020; European Parliament, 2018; Ukrainski et al., 2018). However, due to the lack of empirical evidence, such a predisposition of EU evaluators can solely be hypothesized and is not, in any case, sufficient to explain why some regions located in marginally innovative countries benefit from more evenly distributed participation in EU FPs, whereas others do not.

In the next section, I will present the factors that have possibly influenced this particular situation and speculate on some potentially relevant policy implications.

6 | POLICY IMPLICATIONS AND CONCLUDING REMARKS

To explain why relative innovators play a key role in H2020-NANOTECH, one possibility is that domestic R&D activities, high-tech clusters, and scientific centers of excellence tend to be concentrated in specific and advanced areas of the various countries, which are consequently more equipped for achieving success in competitive transnational innovation networks. This long-term tendency has already been observed in many previous studies, which showed how the regional technological and socioeconomic disparities observed in a country overlap with the level of participation and node positioning in various EU programs related to different programming cycles (e.g., Calignano & Hassink, 2016; Calignano & Quarta, 2015). Although this is common to many EU member states (European Commission, 2020b), the concentration of R&D activities is exacerbated in marginally innovative countries (Lengyel et al., 2015). This factor can help explain the ability of a reasonable number of relative innovators who are situated in less innovative countries ("moderate" or "modest" innovators according to the EIS2020) to hold key positions or join the H2020-NANOTECH core (for a list of all core regions in H2020-NANOTECH, particularly those situated in marginally innovative countries, see Appendix B—Table B1).

Moreover, the discovery of the influence that relative innovativeness may have on holding key or core positions in EU innovation networks is likely to be connected to the lens through which I examined the dataset on transnational collaborations in a critical field, such as nanotechnology, fostered by EU FPs. In other words, these findings were probably latent in previous empirical analyses that addressed the topic of node centrality in EU innovation networks, and I made them explicit by attempting to answer a specific and not previously tackled research question about the importance of being a stronger innovator in a given national context instead of excelling in absolute terms (i.e., at the EU level).

Another important note is regarding the lack of knowledge circulation between regions situated in marginally innovative countries. Although this topic deserves more in-depth attention, what my analysis suggests about the role of the potential gatekeepers (i.e., the relative innovators that can attach to the network core or hold key positions in the surveyed network) is extremely relevant. These key nodes do not trigger knowledge circulation among other domestic regions. Based on the SNA measures applied in this paper, nothing can be said regarding the factors that hinder such knowledge circulation, and some hypotheses can be advanced. However, according to the literature, the most likely scenario is that a significantly different level of absorptive capacity (Cohen & Levinthal, 1990) may hinder knowledge circulation among the various domestic regions (for similar analyses at the cluster and regional levels, see, e.g., Aarstad et al., 2016; Giuliani, 2007; Morrison et al., 2013).

A relevant aspect that should not be neglected is whether similar mechanisms related to absolute and relative innovativeness can be observed in other EU funding schemes. For this purpose, I conducted new econometric analyses based on a data set that I had previously used for an already published article, which aimed at examining whether regional innovativeness ("innovation-driven" participation) or energy demand/vulnerability ("challenge-driven" participation) determines a different degree of participation in research projects tackling energy and, more generally, environmental issues in the H2020 context (Calignano & Trippl, 2020). All my further econometric analyses confirm how relative innovativeness is associated with regional participation and key positioning in H2020 funding schemes addressing different topics and types of actions, whereas absolute innovativeness does not show any statistically significant impact in this respect.[3] This result further validates and strengthens what can be observed in H2020-NANOTECH, thus demonstrating how the findings of the present paper can be confidently extended to other critical research areas targeted by the EU in its programming cycles.

However, the energy projects funded under the H2020 program address domains, such as renewable energies, green technologies, and, more generally, sustainable transition toward a greener economy, which are not dissimilar from the features shown by nanotechnology. In particular, as various authors have argued, the green and renewable energy sectors are complex industries, predominantly characterized by analytic knowledge bases, which rely on multiple knowledge sources and domains, thus making them considerably different from the traditional sectoral knowledge base (Ardito et al., 2019). In other words, despite the additional analyses conducted in a different but related context, it cannot be completely ruled out that the spatial and relational dynamics observed in the EU nanotechnology network are different for other industries characterized by synthetic (e.g., engineering-based industries, such as machinery or food processing) or symbolic (creativity-based industries, such as media, fashion, or computer games) knowledge bases.

In this regard, the geography of innovation networks is largely influenced by the characteristics of each regional socioeconomic fabric (e.g., urban vs. rural regions, core vs. periphery, and institutionally and organizationally thick vs. thin RISs) as well as by the type of industry that mainly characterizes the networked organizations. As mentioned above, nanotechnology is an R&D-intensive science-based industry, thus characterized by an analytic knowledge base, which shows very specific territorial features (high concertation in more developed regions, strong universities, and public/private research infrastructure). Despite the relevance and pertinence of the use of nanotechnology as a background in which the present empirical analysis was conducted (see Section 2.2 for a detailed examination), in such industries, there might be a distinct spatial hierarchy, with only a few regions that possess certain favorable conditions allowing them to join the core of highly competitive international innovation networks. In addition to these spatial considerations, a more sectoral or industrial approach suggests that the organizations primarily characterized by an analytic knowledge base tend to be more engaged than others in innovation networks at various geographical scales (Asheim & Gertler, 2005). Consequently, these elements might have affected the findings presented and discussed in the present paper. Hence, further studies adopting an approach based on differentiated knowledge bases should be conducted in the future, with the aim of testing the robustness of the present empirical analysis against different research and industrial arenas.

A final critical aspect that deserves consideration is that there is a political dimension in the geography of the research networks fostered by EU FPs. As Ukrainski et al. (2018) highlighted, there is a certain tension in the EU research and innovation policy between strengthening the competitiveness of its leading regions and improving the conditions of the less developed regions, which are generally characterized by lower levels of innovativeness. In other words, although the EU evaluators in more recent FPs are more conscious about the importance of overcoming the existing structural differences between the more and less developed EU countries and regions, the apparently unresolved ambivalence between fostering the existing excellences in the core regions and making the organizations operating in the peripheral regions more integrated with EU innovation networks has led to the exacerbation of certain problems largely documented in the ERA (e.g., lacking circulation and low integration of scientific knowledge and technology between the EU member states and their respective domestic regions). Similarly, the low level of participation observed in the less developed EU regions—which seems to be even more pronounced in H2020 than in previous FPs (European Commission, 2018)—is in clear contrast with the objectives of the EU Cohesion Policy (Ukrainski et al., 2018).

The results of this study suggest that a higher level of integration between EU and national research and innovation policies is required. In particular, these actions should aim at integrating not only the relatively innovative regions in FPs, an event documented by my empirical analysis but also most of the less developed regions in countries that are not sufficiently involved in or even completely excluded from the knowledge flows engendered by EU FPs.

In particular, on the EU side, one of the main aims of the H2020 program was to create the so-called "pockets of excellence" (Reid et al., 2015; RISE group, 2017) (i.e., research groups from the countries with the lowest level of participation that might act as national hubs within the respective national contexts and become drivers of change within their own country). The brokerage analysis conducted in the present study shows how this objective has been only partially achieved, with the relatively innovative regions holding a central or strategic position in H2020-NANOTECH while hardly contributing to knowledge circulation within their national boundaries. For this reason, a relevant policy action named "Spreading Excellence and Widening Participation Programme," launched in 2014 under H2020, must be strengthened in the future. This action aims to share good practices among the various countries and support potential applicants, especially those from less developed or marginally innovative countries. According to many participants and analysts, this instrument has not been adequately financed, thus remaining a good intention with little impact from the practical viewpoint. More generally, the various national governments should be more actively involved in decision-making at the EU level and, in turn, work harder in the direction of strengthening their weakly developed national networks, which clearly represent a critical structural barrier for joining the EU research consortia and enhancing the engagement of possible participants (on these topics, see the extensive reports recently issued by the European Commission, 2018; European Parliament, 2018).

In summary, this paper reveals that relative innovativeness matters more than absolute innovativeness in EU innovation networks, and that, consequently, as explicitly mentioned in the title of the paper, "not all peripheries are the same" in the EU context. However, forthcoming studies should aim to definitively clarify whether the various programs or topics addressed by the more recent FP concluded in 2020 have led to more widespread knowledge circulation between the more advanced and less developed EU regions (what the EU aims to achieve through the ERA and its cohesion strategy, which seems to be again missed in the context of EU FPs) by possibly attempting to understand and clarify the mechanisms that hinder knowledge exchange, diffusion, and acquisition in different geographical and sectoral contexts. Finally, a new relevant front of research might regard the role of winning relatively innovative regions in enhancing knowledge circulation (i.e., acting as brokers) within the boundaries of their respective countries.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] The regions included in the final data set were chosen based on their RIS classifications. The level of disaggregation in this specific innovation ranking is NUTS 1 or NUTS2, although in the case of smaller countries, only the national level is considered (NUTS 0 level, i.e., Cyprus, Estonia, Latvia, Luxembourg, and Malta). These countries were included in the network analysis and graph visualization but excluded from the econometric models. This is because relative innovativeness cannot be calculated in these cases, as the country level (NUTS 0) being the maximum level of disaggregation means that making comparisons between regions of the same country is impossible.

[2] For a detailed examination of the indicators that form the RIS and extensive considerations of the pros and cons of using this index in innovation studies with a geographical background, see, for example, Schulze-Krogh and Calignano (2020).

[3] The results of the econometric analyses conducted on the energy projects funded under H2020 can be provided upon request.

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APPENDIX A

DETAILED INFORMATION ABOUT DEPENDENT, INDEPENDENT, AND CONTROL VARIABLES

TABLE A1 Dependent, independent, and control variables: indicators and description

Econometric analysis		
Dependent variables	**Indicator**	**Description**
Participation H2020-NANOTECH	Normalized Degree H2020-NANOTECH	Normalized Degree Centrality (EU Regions): Total number of ties established by each region in the H2020-NANOTECH. Source: Community Research and Development Information Service
Betweenness centrality H2020-NANOTECH	Normalized Betweenness H2020-NANOTECH	Normalized Betweenness Centrality (EU Regions): Key position given by the extent to which a region lies between two other regions in the network. Source: Community Research and Development Information Service
Coreness H2020-NANOTECH	Core-periphery Model H2020-NANOTECH	Categorical core-periphery model based on hill climbing algorithm. Binary variable: 1 = core region; 0 = peripheral region. Source: Community Research and Development Information Service
Independent variables	**Indicator**	**Description**
Absolute and Relative innovativeness	Regional Innovation Scoreboard 2014–2019	Binary variables based on the average score in the Regional Innovation Scoreboard (2014–2019 period) Absolute innovativeness: 1 = regions scoring above the EU average; 0 = regions scoring below the EU average. Relative innovativeness: 1 = regions scoring above the national average; 0 = regions scoring below the national average Source: Regional Innovation Scoreboard 2014–2019
Control variables	**Indicator**	**Description**
Population	Resident population (Log)	Log of the resident population on January 1, 2018. Source: Eurostat
GDP per capita	Real GDP per capita	Ratio of real GDP to the average population (January 1, 2018). Source: Eurostat
Institutions	Quality of government	European Quality of Government Index 2017 issued by the Quality of Government Institute (University of Gothenburg) (Charron et al., 2019). Continuous variable. Source: Regional Competitiveness Index

TABLE A1 (Continued)

Econometric analysis		
Dependent variables	**Indicator**	**Description**
Scientific Excellence	Mentions in the ARWU–na,notechnology	Number of times regional universities are mentioned in the Academic Ranking of World Universities. Five categories: 0 = 0, 1–4 = 1, 5–8 = 2, 9–12 = 3, 13–16 = 4. Subject: Nanoscience and nanotechnology. Years: 2017–2020. Source: Academic Ranking of World Universities
Country	Country fixed effects	Fixed effects/dummy variables. Reference country: Belgium (first country listed in the Regional Innovation Scoreboard)
Other variables (robustness check)	**Indicator**	**Description**
Population Density	Population Density	Log of the number of people per square kilometre
Institutions (binary)	Quality of government	European Quality of Government Index 2017 issued by the Quality of Government Institute (University of Gothenburg) (Charron et al., 2019). Binary variables: 1 = above the EU average/above national average; 0 = below the EU average/below national average. Source: Regional Competitiveness Index
Scientific excellence (binary)	Mention in the ARWU–nanotechnology	Being mentioned once in the Academic Ranking of World Universities. Binary variable: Yes: 1; No = 0. Subject: Nanoscience and nanotechnology. Years: 2017–2020. Source: Academic Ranking of World Universities

APPENDIX B

CORE–PERIPHERY MODEL

TABLE B1 Core and peripheral regions in the H2020-NANOTECH

Core
Région de Bruxelles-Capitale; Vlaams Gewest; Région Wallonne; Yugozapaden; Praha; **Hovedstaden; Stuttgart; Karlsruhe; Freiburg; Tübingen; Oberbayern; Mittelfranken; Schwaben; Berlin; Bremen; Darmstadt; Düsseldorf; Köln; Detmold; Rheinhessen-Pfalz; Dresden; Chemnitz; Schleswig-Holstein; Thüringen; Estonia; Southern; Eastern and Midland;** Kentriki Makedonia; Attiki; Kriti; Galicia; País Vasco; La Rioja; Aragón; Comunidad de Madrid; Castilla y León; Cataluña; Comunidad Valenciana; **Île de France; Nord-Pas de Calais-Picardie; Alsace-Champagne-Ardenne-Lorraine; Languedoc-Roussillon-Midi-Pyrénées; Auvergne-Rhône-Alpes; Provence-Alpes-Côte d'Azur;** Piemonte; Liguria; Lombardia; Veneto; Friuli-Venezia Giulia; Emilia-Romagna; Toscana; Lazio; Campania; Cyprus; Budapest; **Groningen; Overijssel; Gelderland; Utrecht; Noord-Holland; Zuid-Holland; Noord-Brabant; Limburg; Ostösterreich; Südösterreich; Westösterreich;** Warszawski stoleczny; Norte; Lisboa; Bucuresti-Ilfov; Zahodna Slovenija; **Helsinki-Uusimaa; Länsi-Suomi; Pohjois- ja Itä-Suomi; Stockholm; Östra Mellansverige; Västsverige; Övre Norrland; North East; North West; Yorkshire and The Humber; East Midlands; West Midlands; East of England; London; South East; South West; Wales; Scotland**
Periphery
Severozapaden; Severen tsentralen; Severoiztochen; Yugoiztochen; Yuzhen tsentralen; Strední Cechy; Jihozápad; Severozápad; Severovýchod; Jihovýchod; Strední Morava; Moravskoslezsko**; Sjælland; Syddanmark; Midtjylland; Nordjylland; Niederbayern; Oberpfalz; Oberfranken; Unterfranken; Brandenburg; Hamburg; Gießen; Kassel; Mecklenburg-Vorpommern; Braunschweig; Hannover; Lüneburg; Weser-Ems; Münster; Arnsberg; Koblenz; Trier; Saarland; Leipzig; Sachsen-Anhalt; Northern and Western;** Anatoliki; Makedonia, Thraki; Dytiki Makedonia; Ipeiros; Thessalia; Ionia Nisia; Dytiki Ellada; Sterea Ellada; Peloponnisos; Voreio Aigaio; Notio Aigaio; Principado de Asturias; Cantabria; Comunidad Foral de Navarra; Castilla-la Mancha; Extremadura; Illes Balears; Andalucía; Región de Murcia; Ciudad Autónoma de Ceuta; Ciudad Autónoma de Melilla; **Centre-Val de Loire; Bourgogne-Franche-Comté; Normandie; Pays de la Loire; Bretagne; Aquitaine-Limousin-Poitou-Charentes; Corse;** Jadranska Hrvatska; Kontinentalna Hrvatska; Valle d'Aosta; Provincia Autonoma Bolzano; Provincia Autonoma Trento; Umbria; Marche; Abruzzo; Molise; Puglia; Basilicata; Calabria; Sicilia; Sardegna; Latvia; Sostinės regionas; Lietuvos regionas; **Luxembourg;** Pest Közép-Dunántúl; Nyugat-Dunántúl; Dél-Dunántúl; Észak-Magyarország; Észak-Alföld; Dél-Alföld; Malta; **Friesland; Drenthe; Flevoland; Zeeland;** Malopolskie; Slaskie Wielkopolskie; Zachodniopomorskie; Lubuskie; Dolnoslaskie; Opolskie; Kujawsko-Pomorskie; Warminsko-Mazurskie; Pomorskie; Lódzkie; Swietokrzyskie; Lubelskie; Podkarpackie; Podlaskie; Mazowiecki regionalny; Algarve; Centro; Alentejo; Nord-Vest; Centru; Nord-Est; Sud-Est; Sud—Muntenia; Sud-Vest Oltenia; Vest; Vzhodna Slovenija; Bratislavský kraj; Západné Slovensko; Stredné; Slovensko; Východné; Slovensko; **Etelä-Suomi; Åland; Småland med öarna; Sydsverige; Norra Mellansverige; Mellersta Norrland; Northern Ireland**

Note: Regions situated in countries classified as “leader” and “strong” innovators in the EIS2020 are highlighted in bold.

APPENDIX C

ROBUSTNESS TESTS

TABLE C1 Binary logistic regression (robustness test). Dependent variable: core-periphery model

	Model 7: robustness test		
		95% CI	
		Lower	Upper
Absolute innovativeness	1.11 (0.68) 3.03	0.79	11.56
Population density (log)	0.71 (0.43) 2.03	0.85	4.83
GDP per capita	0.68* (0.26) 1.97	1.17	3.31
Quality of institutions$_{(binary/EU)}$	−1.05 (0.68) 0.35	0.09	3.21
Scientific Excellence $_{(binary)}$	2.60** (0.44) 13.42	5.63	31.98
Constant	−4.92** (1.01)		
Hosmer-Lemeshow test	5.26		
Pseudo R^2	.43		
No. of EU regions	216		

Note: Standard errors in parentheses; odds ratios below the standard errors.

**Statistically significant at the .01 level; *statistically significant at the .05 level.

TABLE C2 Binary logistic regression (robustness test). Dependent variable: Core-periphery model

	Model 8: robustness test	95% CI	
		Lower	Upper
Relative innovativeness	1.32**	1.62	8.76
	(0.43)		
	3.77		
Population density (log)	0.48	0.63	4.17
	(0.48)		
	1.62		
GDP per capita	0.55*	1.04	2.88
	(0.26)		
	1.73		
Quality of institutions$_{(\text{binary/nat.})}$	−0.71	0.21	1.15
	(0.43)		
	0.49		
Scientific excellence$_{(\text{binary})}$	2.59**	5.72	30.78
	(0.43)		
	13.28		
Constant	−4.39**		
	(1.09)		
Hosmer-Lemeshow test	5.84		
Pseudo R^2	.45		
No. of EU regions	216		

Note: Standard errors in parentheses; odds ratios below the standard errors.

**Statistically significant at the .01 level; *statistically significant at the .05 level.

TABLE C3 Tweedie model with country fixed effects (reference country: Belgium). Dependent variables: degree (Models 9 and 10) and between (Models 11 and 12)

	Robustness test			
	Model 9	**Model 10**	**Model 11**	**Model 12**
	Degree	**Degree**	**Between.**	**Between.**
Above EU average	0.36		0.69	
	(0.27)		(0.47)	
Above National average		0.74**		1.13**
		(0.15)		(0.23)
Population density$_{(log)}$	0.24	0.10	0.73**	0.44
	(0.17)	(0.17)	(0.23)	(0.24)
GDP per capita	0.27**	0.14	0.50**	0.39**
	(0.08)	(0.09)	(0.11)	(0.12)
Quality of institutions$_{(binary/EU)}$	−0.17		−0.34	
	(0.42)		(0.58)	
Quality of institutions$_{(binary/nat.)}$		−0.32		−0.51**
		(0.13)		(0.07)
Scientific excellence$_{(binary)}$	0.76**	0.59**	1.77**	1.50**
	(0.16)	(0.15)	(0.24)	(0.24)
Country fixed effects	Yes	Yes	Yes	Yes
Constant	−3.01**	−2.16**	−5.80**	−4.66**
	(0.95)	(0.55)	(1.40)	(1.38)
Likelihood χ^2	124.23**	147.83**	218.57**	242.36**
No. of EU regions	216	216	216	216

Note: Standard errors in parentheses.

**Statistically significant at the .01 level

APPENDIX D

BROKERAGE ANALYSIS

TABLE D1 Brokerage scores: gatekeepers and coordinators. Targeted countries: Remaining EU countries

Country	EIS2020	Region	Gatek.	Coord.
Belgium	Strong	Région de Bruxelles-Capitale	63	0
		Vlaams Gewest	56	0
		Région Wallonne	11	0
Czechia	Moderate	Praha	165	2
		Strední Cechy	0	0
		Jihozápad	0	0
		Severozápad	0	0
		Severovýchod	0	0
		Jihovýchod	4	0
		Strední Morava	0	0
		Moravskoslezsko	0	0
Denmark	Leader	Hovedstaden	414	6
		Sjælland	18	0
		Syddanmark	0	0
		Midtjylland	116	0
		Nordjylland	16	0
Germany	Strong	Stuttgart	847	242
		Karlsruhe	779	256
		Freiburg	349	122
		Tübingen	351	80
		Oberbayern	1766	416
		Niederbayern	37	8
		Oberpfalz	30	8
		Oberfranken	56	16
		Mittelfranken	434	154
		Unterfranken	96	18
		Schwaben	180	30
		Berlin	1149	396
		Brandenburg	9	0
		Bremen	305	126
		Hamburg	98	30
		Darmstadt	386	112
		Gießen	5	0
		Kassel	0	0
		Mecklenburg-Vorpommern	1	0

(Continues)

TABLE D1 (Continued)

Country	EIS2020	Region	Gatek.	Coord.
		Braunschweig	143	44
		Hannover	50	10
		Lüneburg	0	0
		Weser-Ems	22	8
		Düsseldorf	814	220
		Köln	959	234
		Münster	68	24
		Detmold	213	58
		Arnsberg	128	28
		Koblenz	0	0
		Trier	0	0
		Rheinhessen-Pfalz	490	240
		Saarland	115	10
		Dresden	486	130
		Chemnitz	247	126
		Leipzig	149	36
		Sachsen-Anhalt	1	0
		Schleswig-Holstein	95	32
		Thüringen	484	116
Ireland	Strong	Northern and Western	7	0
		Southern	66	0
		Eastern and Midland	127	0
Spain	Moderate	Galicia	76	0
		Principado de Asturias	14	0
		Cantabria	0	0
		País Vasco	611	48
		Comunidad Foral de Navarra	18	2
		La Rioja	108	8
		Aragón	208	18
		Comunidad de Madrid	537	26
		Castilla y León	282	26
		Castilla-la Mancha	35	6
		Extremadura	0	0
		Cataluña	585	26
		Comunidad Valenciana	184	6
		Illes Balears	0	0
		Andalucía	112	6
		Región de Murcia	0	0
		Ciudad Autónoma de Ceuta	0	0
		Ciudad Autónoma de Melilla	0	0

TABLE D1 (Continued)

Country	EIS2020	Region	Gatek.	Coord.
France	Strong	Île de France	655	34
		Centre-Val de Loire	35	4
		Bourgogne-Franche-Comté	3	0
		Normandie	0	0
		Nord-Pas-de-Calais—Picardie	163	6
		Alsace-Champagne-Ardenne—Lorraine	62	0
		Pays de la Loire	22	2
		Bretagne	0	0
		Aquitaine—Limousin—Poitou-Charentes	91	12
		Languedoc-Roussillon—Midi-Pyrénées	122	4
		Auvergne—Rhône-Alpes	552	50
		Provence-Alpes-Côte d'Azur	77	4
		Corse	0	0
Croatia	Moderate	Jadranska Hrvatska	0	0
		Kontinentalna Hrvatska	0	0
Italy	Moderate	Piemonte	702	68
		Valle d'Aosta/Vallée d'Aoste	0	0
		Liguria	196	8
		Lombardia	767	80
		Provincia Autonoma Bolzano/Bozen	0	0
		Provincia Autonoma Trento	64	8
		Veneto	511	38
		Friuli-Venezia Giulia	227	36
		Emilia-Romagna	619	46
		Toscana	440	36
		Umbria	2	0
		Marche	2	0
		Lazio	975	90
		Abruzzo	25	6
		Molise	0	0
		Campania	159	16
		Puglia	17	0
		Basilicata	8	2
		Calabria	6	0
		Sicilia	7	0
		Sardegna	0	0
Lithuania	Moderate	Sostinės regionas	0	0
		Lietuvos regionas	0	0

(Continues)

TABLE D1 (Continued)

Country	EIS2020	Region	Gatek.	Coord.
Hungary	Moderate	Budapest	292	6
		Pest	0	0
		Közép-Dunántúl	0	0
		Nyugat-Dunántúl	0	0
		Dél-Dunántúl	0	0
		Észak-Magyarország	0	0
		Észak-Alföld	0	0
		Dél-Alföld	16	2
Netherlands	Leader	Groningen	67	0
		Friesland	0	0
		Drenthe	2	0
		Overijssel	120	0
		Gelderland	383	28
		Flevoland	0	0
		Utrecht	164	0
		Noord-Holland	136	0
		Zuid-Holland	460	12
		Zeeland	0	0
		Noord-Brabant	335	14
		Limburg	157	0
Austria	Strong	Ostösterreich	61	0
		Südösterreich	47	0
		Westösterreich	18	0
Poland	Moderate	Malopolskie	33	2
		Slaskie	2	0
		Wielkopolskie	5	0
		Zachodniopomorskie	0	0
		Lubuskie	0	0
		Dolnoslaskie	13	2
		Opolskie	0	0
		Kujawsko-Pomorskie	0	0
		Warminsko-Mazurskie	0	0
		Pomorskie	0	0
		Lódzkie	54	2
		Swietokrzyskie	0	0
		Lubelskie	0	0
		Podkarpackie	0	0
		Podlaskie	0	0
		Warszawski stoleczny	353	20
		Mazowiecki regionalny	40	2

TABLE D1 (Continued)

Country	EIS2020	Region	Gatek.	Coord.
Portugal	Moderate[a]	Norte	178	2
		Algarve	0	0
		Centro	15	0
		Lisboa	171	2
		Alentejo	4	0
Slovenia	Moderate	Vzhodna Slovenija	11	0
		Zahodna Slovenija	67	0
Slovakia	Moderate	Bratislavský kraj	0	0
		Západné Slovensko	0	0
		Stredné Slovensko	0	0
		Východné Slovensko	0	0
Finland	Leader	Helsinki-Uusimaa	186	0
		Etelä-Suomi	15	0
		Länsi-Suomi	88	0
		Pohjois- ja Itä-Suomi	82	0
		Åland	0	0

[a]Portugal became a "strong" innovator in 2020, but it was considered as a "moderate" innovator in this study based on how the country was classified in all the other editions of the EIS published throughout the H2020-NANOTECH program.