Power relations in European RDI-collaboration networks. Disparities in policy-driven opportunities for knowledge generation in ICT

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ABSTRACT
Due to their potential for economic growth and development, the enabling technologies of the digital transformation, ICT and complementary fields such as advanced robotics, artificial intelligence and smart systems integration, are high on the innovation policy agenda of the EU. A strong innovative performance of the EU in this technology field depends inter alia on the extent to which the bundling of resources for innovative activities is achieved and disparities in innovative activities between its member states are overcome. Focusing on Horizon 2020, we trace disparities of knowledge generation in ICT across the geographical dimension and the network dimension. We apply descriptive and analytical statistics as well as network analysis to the CORDIS database and connect our findings to the distribution of power between EU member states and other countries associated with Horizon 2020. We then investigate whether there is power-law behaviour in our empirical data. We find a rather unequal distribution of power between countries that manifests in country size, per capita income and member status in the EU. Future innovation policy needs to prioritise a more cohesive and egalitarian European knowledge base in this strategic technology field and cope with the current imbalances in the distribution of power.

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1. Introduction
The digital transformation is characterised by deep changes in different realms of society. A strong innovative performance in its enabling technologies – the new information and communication technologies (ICT) as well as complementary technologies, including advanced robotics, artificial intelligence, and smart systems integration – is a strategic policy objective of global economic key players like China, the U.S., and the EU. This is considered as important not least because this technology field is a catalyst for economic growth, has a wide application potential and far-reaching transformative capacities. In this regard, the stock of resources made available for innovative activities as well as the capability to use it are important determinants of the innovative performance. According to Boudon and Bourricaud (1989), these two are elements of a country’s power status too (see also Tellis et al. [2000]). Understood in this way, there is thus a clear link between the capability to generate and exploit profitably new knowledge in the form of innovation and a country’s power status.
Focusing on European policy efforts in ICT, for several years the EU has introduced a range of different innovation policies that aim at bundling resources for innovative activities and currently, the development of this technology field is promoted in the Europe 2020 strategy. The main policy instrument in this regard is the 8th European framework programme for research and innovation, i.e. Horizon 2020 (FP8). The emphasis on directing innovation in ICT and their large-scale funding under FP8 can be considered as a policy effort to strengthen the EU’s power position and competitiveness in this field vis-à-vis global competitors. However, its success depends inter alia on the extent to which the bundling of resources is achieved and disparities in innovative activities within the EU, between its member states, are overcome. Since we emanate from power being determined by the resources acquired and the capability to use them, the question of the distribution of power between countries boils down to the question of whether there exist disparities in countries’ resources capacity as well as in their opportunities to innovate. Against this background, in this paper we answer the following research questions: Which disparities in the distribution of resources for knowledge generation in ICT do exist under Horizon 2020? Will the current distribution of power between countries in terms of access to funding and the capability to use it fuel a situation of oligarchic tendencies, with the most powerful countries getting even more powerful? Finally, what are the policy implications for the ‘Europeanisation of innovation’ in ICT?

To answer these questions, we revert to descriptive and analytical statistics as well as network analysis, and study disparities in innovative activities in ICT under FP8 across the geographical and the network dimension, with the latter being at the centre of our research. We measure disparities in knowledge generation across the geographical dimension by the distribution of EU-funding for innovative activities in ICT and the number of actors involved in research, development, and innovative (RDI-)projects. The ability to use these resources and disparities therein are traced across the network dimension. To obtain additional insights into these disparities, we investigate whether they manifest themselves in specific country characteristics, such as per capita income, population size, member status in the EU (EU-15 vs. EU-13), and funding status in ICT under the European structural and investment funds (ESIF). To complete the picture, we finally explore whether there is power-law behaviour in our empirical data.

The main contributions of this paper are the following: First, we provide an analysis of disparities in innovative activities centred on ICT and thereby improve the empirical basis in this strategic technology field. Second, we substantiate empirically the theoretical concept of power introduced by Boudon and Bourricaud (1989). Third, we represent cross-country RDI-collaboration as an edge-weighted and directed graph. Especially, the latter property allows us to keep relevant information on the role of actors in project consortia (coordinator versus participants), providing a more detailed picture of the power status of countries in knowledge generation in ICT. Finally, we carry out our analysis on FP8 data, which up until now have been hardly used in empirical studies of this issue.

The paper is structured as follows: Section 2 highlights the policy context of our research topic and places our study in the relevant literature. Section 3 contains information on the dataset exploited and related preparatory work. Section 4 is the main part of our work; it introduces the method used and includes empirical results. Section 5 discusses the relevance of our findings for policy and concludes. Some additional material can be found in the Appendix.

2. Policy context and background literature: a brief survey

2.1. The treatment of the key technology field ICT in current EU policy

For many years, ICT have been high on the EU’s innovation policy agenda. Already in 2000, when the European Research Area (ERA) was initiated, innovation in ICT and their use for stimulating innovation in other technology fields were strongly promoted. More recently, this technology field has been prioritised under Europe 2020, the mission of which is to achieve ‘smart, sustainable and inclusive growth’. ICT are important for accomplishing this mission and take a key role in five out of the
seven flagship initiatives\textsuperscript{1} that make up Europe 2020: While the notion of ‘smart growth’ aims at a transition towards a knowledge- and innovation-based European society ‘making full use of information and communication technologies’ (EC 2010, 11–12), ICT are also considered a crucial factor for a sustainable transport and energy infrastructure, thereby supporting the vision of a resource-efficient and green economy (ibid.). On top of that, the use of ICT should foster social and economic inclusion for a cohesive European society.

The funding for knowledge generation and innovation in ICT as planned out in the Europe 2020 strategy is to a large extent covered by Horizon 2020, which has a total funding volume of almost 80 billion Euro, and compared to FP7 the funding volume spent on ICT increased by 25%. Funding for ICT is accounted for under each pillar I–III (Excellent Science, Industrial Leadership and Societal Challenges) and in each of the three work programmes (i.e. work programmes 2014–2015, 2016–2017 and 2018–2020). Innovative activities under Horizon 2020 are project-based and for the three work programmes calls for proposals are launched regularly. Actors – these can be private companies, research organisations, higher and secondary education establishments, public bodies as well as others – apply for funding under a specific call through submitting a project proposal which contains a unique funding methodology. As to the function of actors, two are usually distinguished: the coordinator and the participant. Unlike the latter, it is the role of the coordinator to initiate the project proposal, to lead the communication with the European Commission (EC) and to design the project outline and the allocation of tasks and the budget. Once the proposal is approved, they monitor the project. Funding for innovation in ICT under Horizon 2020 is activity-oriented and these activities can be of a different type, spanning the various stages of the innovation cycle – from basic and applied research, technology development and integration, up to more close-to-market activities (EC 2013, 2015, 2017a).

Horizon 2020 encourages international cooperation, though actors only qualify for receiving funding if they are from EU member states and their overseas territories, associated countries as well as non-EU countries that are automatically eligible for funding. Projects can be either individual researcher projects or consortia, whereby the size and rules for the composition of a project are subject to the type of action. Depending also on the type of action, different funding rates apply, and RDI-projects are co-financed by the EU and actors. Evaluation criteria in the selection process can be summarised as ‘excellence, impact, and quality and efficiency of implementation’. If agreed upon, the do’s and don’ts of a project are specified in the consortium agreement. In general, obtaining funding under Horizon 2020 is a highly competitive process and the overall success rate is very low – only about 15%. (See Horizon 2020 Online Manual for details on these structural characteristics of the 8th European framework programme for research and innovation).

\textbf{2.2. Previous research}

Current EU innovation policy aims at the Europeanisation of innovation and seeks to align innovation policy across member states. The bundling of resources is expected to increase the EU’s innovative capability and improve competitiveness in the respective technology field. This is based on the presumption that first, knowledge generation is a collective rather than an individual process, and second, the profitable use of knowledge in the form of innovation is the engine of economic growth and development. Understood in this way, intense knowledge flows between innovative actors, for instance in the form of project-based collaboration, allow for economies of scale, network effects, and knowledge spillovers (see, e.g., Aghion and Jaravel [2015] for an overview). Unequal access to resources for innovative activities between actors and disparities in the capability to use them, however, prevents exploiting the full innovative potential of the bundling of resources and may be obstructive to the innovative performance. Such disparities in innovative activities can be studied across different spatial dimensions, the most common ones being the network dimension and the geographical dimension (see Autant-Bernard et al. [2007]). There is a considerable body of literature in the economics of innovation, regional science, and economic geography, that accounts
for these two dimensions in the analysis of disparities in innovation and that addresses different aspects of power relations under the FPs and other funding tools.

Focusing on the network dimension, of particular interest for our research purpose is an early study by Breschi and Cusmano (2004), who define an ‘oligarchic core’ as consisting of those key actors in collaborative efforts of knowledge generation under FP3 and FP4, who have taken leadership over time, in the sense that removing them from the network would severely disrupt knowledge flows and communication. This notion meets with our understanding of power as the capability of using resources for innovative activities, whereas we seek to identify influential innovative actors (i.e. knowledge hubs) in a slightly different way, namely by the frequency of participation in project consortia (see also Protogerou, Caloghirou, and Siokas 2010). Another relevant study was conducted by Roedinger-Schluger and Barber (2008) who find the networks of collaboration related to the first five FPs to be scale-free and complex and sharing a small-world property. What they identify as important for future research and where our study can contribute, is the necessity of investigating ‘the additional information included in edge weights’ (ibid., 23). Thus, in our study where networks are edge-weighted, we look at the intensity of collaboration as one central aspect of the bundling of resources. Moreover, we derive the test of a power-law distribution from this linkage-based framework, which allows us to discuss the results against the background of the intensity of collaboration in RDI. Close to our approach with regard to the specific technology case, but for FP6, is a study by Breschi et al. (2009), where the authors concentrate on knowledge diffusion in ICT within policy-driven networks. In a more recent publication, for the case of Italy, oligarchic tendencies in a network and the presence of a ‘Matthew effect’ – another aspect of power – were highlighted by Antonelli and Crespi (2013). Addressing the issue of power in knowledge generation in the context of Horizon 2020, Enger and Castellacci (2016) find persistence of actors in participation of RDI-projects and they empirically confirm that prior funding and the reputation of the applying organisation are important determinants of successful granting. Published in this journal, though the focus was not on Horizon 2020 but on the Technological Argentinian Fund, Pereira and Suárez (2018) test whether different forms of public funding for innovation (non-refundable grants, subsidised loans and tax credits) lead to a Matthew effect. Two aspects where we depart from these papers are first, we do not explicitly account for the time dimension in our study and second, in most cases, we interpret our data at the country level, though we implicitly account for the level of actors. What we share with them is the focus on power relations in innovative activities and differentials in the distribution of power. Similar to their methodological approach, we also use descriptive and analytical statistics to test whether there is power-law behaviour in the empirical data.

Turning to the second spatial dimension of disparities in innovation, there is a rich literature that focuses on the geography of European collaborative RDI-efforts and this is sometimes combined with a network dimension. Like our study, these works are based on the premise that cross-country collaboration in innovative activities via networks is favourable to the innovative capability and performance. Frequently tools of network analysis are applied together with spatial econometrics to assess various aspects of the integration of RDI-efforts across Europe. Different types of networks based on project-based collaboration, co-publication or co-patenting or a mixture thereof are used in the following fields: (i) exploring the effects of geographical and network proximity on inter-regional RDI-collaboration (Maggioni and Uberti 2009; Bergé 2015) or Hoekman, Frenken, and van Oort (2009)); (ii) studying the impact of the FPs and other innovation policy instruments on regional convergence in the EU and the relationship between the FPs and European cohesion policy (see, e.g., De Noni, Orsi, and Belussi [2018]; Pontikakis et al. [2018]; or Ukrainski et al. [2018]); (iii) investigating the integration processes under European cooperative agreements of knowledge generation (Lata, Scherngell, and Brenner [2015]; Scherngell and Lata [2011] or Makkonen and Mitze [2016]); and (iv) dealing with the space–time impact of European regions’ network positioning on knowledge generation (e.g. Wanzenböck and Piribauer [2017]) etc.

In this paper, we are not so much concerned with exploring the aspect of whether the geographical distance between actors plays a role for collaborative efforts of knowledge generation, but rather
concentrate on the distribution of resources for knowledge generation across geography and the specific patterns that manifest themselves in this regard. Moreover, technology-specific analyses of disparities in policy-driven opportunities for knowledge generation are rare, with notable exceptions such as e.g. Wanzenböck, Scherngell, and Lata (2015) or Wanzenböck, Neuländtner, and Scherngell (2020). In any case, such a fine-grained analysis is important because the character of knowledge generation varies between technologies (see, e.g., Pavitt [1984] or Castellacchi [2008]) and insights into technology-specific patterns facilitate the development of tailor-made innovation policies. With our focus on ICT, we contribute to filling this gap. Besides, in this strand of literature, the inter-regional RDI-collaboration networks are based on the actor level, though they are frequently interpreted at the country level. We also follow this approach. Yet, in none of the mentioned works RDI-collaboration networks are represented as directed graphs (if at all as weighted ones). However, it is not just the intensity of collaboration that matters. We consider the distinction between the different functions of actors in project consortia – coordinators versus participants – as equally important, since they amount to fundamentally different roles which actors play in the networks and which influence power at the country level, as emphasised by Breschi and Cusmano (2004). Finally, through distinguishing various country characteristics in which disparities in the distribution of resources for innovative activities may unfold, we are close to Paier and Scherngell (2011), Amoroso, Coad, and Grassano (2017), Wanzenböck, Scherngell, and Brenner (2014) and Wanzenböck, Scherngell, and Lata (2015), who also account for regional characteristics and look at the region-specific determinants of RDI-collaboration.

3. Data

The main data source for our empirical study is CORDIS, which is freely accessible from the EU Open Data Portal (EU 2012). Two data files downloaded from CORDIS on January 24th 2019 with detailed information on FP8 (1) projects and (2) organisations served as the basis for constructing the relevant dataset. As we focus in our empirical analysis on RDI-activities in ICT, we retrieve – via project calls – from the two data files just those projects, respectively actors, which are identified in work programmes 2014–2015, 2016–2017 and 2018–2020 as explicitly addressing ICT topics (EC 2013, 2015, 2017a). The projects are funded under each of the three pillars I-III of FP8 and can be partitioned into a more fine-grained structure describing the different calls and thus subfields of innovative activities.

From the basic data files, we extracted those projects that have either the status ‘signed’ or ‘closed’ and excluded the ones that are terminated and hence are stopped before their scheduled end. In our empirical investigation, we concentrate on actors that are still actively involved in a project. More than 98% of actors reside in EU-28 member states or in six Non-EU countries that are associated with Horizon 2020 (Iceland, Israel, Norway, Serbia, Switzerland, and Turkey). All remaining actors (and projects) were included in a rest group termed ‘other countries’ and therefore we work with a total country sample of 35 entities.

Regarding country characteristics, we used some further data: First, to partition countries in our sample according to size, we used population data from the World Bank (2017). In our definition, a ‘small’ country has a population size of less than or equal to 30 million, whereas ‘large’ countries have a population size of more than 30 million (see Appendix, Table A1). Second, to group countries according to their income, we took data on GDP per capita in current US dollar from the World Bank (2017) and averaged this over the years 2014–2017. There shows to be a natural division in our country sample, and we define ‘low-income’ countries as those with a GDP per capita of less than 20,000 US dollar, ‘middle-income countries’ account for a GDP per capita of less than 40,000 US dollar, and ‘high-income countries’ in our sample correspond to those with a GDP per capita of more than 40,000 US dollar. To rank countries according to the intensity of funding for ICT received from the ESIF, the dataset ‘Finance Implementation by Theme vs Member State’ was taken from the corresponding database of the ESIF (EC 2019). Again, for this variable, there is a relatively natural
division in the country sample: Those countries receiving less than 250 Mio. Euro belong to the category ‘low’, those between 250 and 500 Mio. Euro conceive of ‘medium’ funding intensity and finally, we attribute the status ‘high’ to those countries which acquire more than 500 Mio. Euro funding for ICT from the ESIF. Note that some countries are classified as ‘n.a.’, as they are not included in the dataset underlying this classification. The different country characteristics are summarised in Table A1 in the Appendix.

To get rid of the scale effect in our networks, as required for testing for a non-normal, power-law distribution, we used the variable ‘human resources in science and technology (HRST) as a percentage of the active labour force’ from Eurostat (2019). This, after multiplying by the absolute size of the active labour force, was averaged over the years 2014–2017. In order to get absolute numbers, the size of the active labour force for Israel, Iceland, Norway, Serbia and Turkey was taken from ILOSTAT (2019) as this is not published by Eurostat (2019). The variable HRST is available for all countries of our sample except for Israel. To calculate a suitable proxy for Israel we consulted the EIS Database (2018) and used the 2014–2017 average of the variable ‘human resources’ and inspected which other countries reached a similar level in this regard. Then we took the average of these countries’ level of HRST to obtain the missing value for Israel.

4. Method and empirical findings

4.1. Descriptive statistics

Altogether 3,549 RDI-projects related to ICT have been funded from 2014 until January 2019 across our country sample in which 18,967 actors have been involved, either as coordinators (3,549) or as participants (15,418). The RDI-projects have received funding from the EU of almost 7.5 billion Euro, which is more than 86% of total project costs; the remaining share of project costs has been borne by actors themselves.

Many different subfields have been defined within the scope of RDI-funding for ICT, signalling the generic character of this technology field (see Table 1). By far the largest share of RDI-efforts is carried out under pillar II. Taking a closer look at pillar II, an outstanding number of RDI-projects is financed by the small- and medium-sized enterprise instrument, offering support for innovative activities of SMEs. Also, the pillar I subfield future and emerging technologies, in which highly risky, visionary and radical innovation is supported, as well as the three pillar II subfields, the future internet, content technologies and information management and cross-cutting activities, capture a significant share in total projects funded in ICT. A slightly different picture emerges for actors involved in these projects and the volume of EU-funding, where different subfields stand out and account for high shares in terms of resources allocated (see Table 1). Taken together, policymakers push knowledge generation in ICT especially under pillar II and direct innovative activities and the resources required therefor into projects with a strong industrial dimension. This reflects the importance of ICT for enhancing the EU’s competitiveness in developing industrial key technologies.

4.2. Disparities in the allocation of resources across geography

Turning to the geographical dimension of innovative activities in ICT under FP8, Figure 1 (Panel (a) and (b)) illustrates that there is a substantial divide in the allocation of resources for RDI-efforts across our country sample. This gets evident too if looking at the corresponding Lorenz curves, where the Gini-coefficients reach a level of 0.594 for actors involved in RDI-projects and of 0.638 for financial support by the EU (see Figure 2 Panel (a) and (b)). The available stock of resources for knowledge generation in ICT varies thus significantly between countries and we find various disparities: Only a handful of countries are able to attract large-scale EU-funding and dispose of a considerable number of actors while others are lagging behind. As can be seen from Figure 1, there is a pronounced scale effect, as the middle- and high-income, large, old member states of
the EU, viz. Germany, France, Spain, Italy and the United Kingdom, account for the top-5 ranking positions with regard to the stock of financial and human resources employed in project consortia. Spain and Italy also intensively acquire funding from the ESIF dedicated to RDI-efforts in ICT, where as this is not the case for the UK and Germany, illustrating that the similarity of these frontrunners under Horizon 2020 is not mirrored in the latter policy instrument that explicitly fosters cohesion.

Apart from the observed scale effect, another significant disparity exists between old member states and the EU-13: Except for Poland, this group of countries possesses of only a small stock of resources and different to the EU-15, new member states are rather peripheral regarding RDI-efforts in ICT and the corresponding subfields under FP8. Some of the associated countries, such as Norway or Israel, even account for a higher stock of resources (in both variables) than the average of the EU-13 member states.

In a nutshell, access to funding under Horizon 2020 and the employment of the required innovative actors is clearly related to the member status in the EU and to country size as well as income – some of the small, high-income old EU-member countries have above equi-distributional shares in one and/or both variables too, including the Netherlands, Belgium and Sweden. The same conclusions, however, cannot be so unambiguously drawn when looking at the intensity of participation under ESIF.

### Table 1. Descriptive statistics of RDI-activities in ICT. Deviations from 100% are due to rounding.

| Subfields and technology subfields | Share of projects in total no. of projects (in %) | Share of actors in total actors (in %) | Share of EU-funding in total EU-funding (in %) |
|------------------------------------|-----------------------------------------------|----------------------------------------|-----------------------------------------------|
| **Pillar I: Excellent Science**     |                                               |                                        |                                               |
| future and emerging technologies   | 8.3                                           | 15.3                                   | 17                                            |
| research infrastructure            | 6.1                                           | 8.2                                    | 10.6                                          |
| **Pillar II: Industrial Leadership**|                                               |                                        |                                               |
| next generation internet/future internet | 5.4                                       | 9.9                                    | 9.5                                           |
| a new generation of components and systems | 1.5                                       | 2.7                                    | 3.1                                           |
| advanced computing and cloud computing | 0.9                                       | 1.6                                    | 1.9                                           |
| European data infrastructure       | 0.1                                           | 0.1                                    | 0.2                                           |
| SME/horizontal ICT innovation actions | 55.3                                      | 11.2                                   | 11                                            |
| fast track to innovation pilot     | 1.8                                           | 1.5                                    | 1.9                                           |
| technologies for digitising European industry/digitising and transforming European industry and services | 0.1 | 0.2 | 0.2 |
| micro- and nanoelectronic technologies, photonics | 3.1 | 5 | 6 |
| robotics and autonomous systems    | 1.5                                           | 2.1                                    | 2.5                                           |
| content technologies and information management | 4.1 | 7.4 | 6.4 |
| factories of the future            | 1.6                                           | 4                                      | 4.1                                           |
| cross-cutting activities           | 3.2                                           | 8.8                                    | 9.2                                           |
| international cooperation          | 1.3                                           | 1.8                                    | 1                                             |
| diverse                            | 0.2                                           | 0.2                                    | 0.1                                           |
| **Pillar III: Societal Challenges**|                                               |                                        |                                               |
| health, demographic change and wellbeing | 11.5                                      | 27.8                                   | 25.1                                          |
| food security, sustainable agriculture and forestry, marine and maritime and inland water research and the bioeconomy | 0.3 | 1.7 | 1.2 |
| secure, clean and efficient energy | 2.2                                           | 5.7                                    | 7                                             |
| smart, green and integrated transport | 1.6                                       | 4.5                                    | 3.7                                           |
| climate action, environment, resource efficiency and raw materials | 1.1 | 3.3 | 2.3 |
| Europe in a changing world – inclusive, innovative and reflective societies | 1.6 | 3 | 2.2 |
| secure societies – protecting freedom and security of Europe and its citizens | 1.9 | 3.9 | 3.5 |

Note that the subfield ‘diverse’ of pillar II constitutes a rest group including calls which only account for a tiny number of RDI-projects, viz. platforms and pilots, cybersecurity, innovation and entrepreneurship support, responsibility and creativity. Similarly, this is the case for the subfield ‘cross-cutting activities’. Authors’ calculations.
Shifting the perspective to innovative activities carried out under the single pillars I-III (see Table 2), the Gini-coefficient takes the highest level for RDI-activities in Excellent Science in both variables, indicating that especially in academia there is an agglomeration of resources and specific ‘circles of excellence’ benefiting from this funding mechanism exist. This result probably also stems from the fact that historically grown hubs of academic science have evolved that perceive of a comparative advantage in the acquisition of large-scale project funding and dispose of the infrastructure necessary to conduct complex RDI-projects. Slightly less concentrated are resources for knowledge generation carried out under pillar II. Finally, innovative activities under pillar III are comparatively most dispersed and disparities are thus lowest among the countries involved.

**Figure 1.** Geographical distribution of (1) actors involved in RDI-projects (Panel (a)) and (2) EU project-funding for RDI-projects (Panel (b)) in ICT. The maps were drawn with the freeware StatPlanet. Authors’ illustrations.
Taking a closer look at the subfield level of each pillar, further disparities in the geographical allocation of resources get evident. Especially for the EU-13, some similarities are observable that contrast them from the rest of our country sample: In Excellent Science RDI-projects in research infrastructure are particularly strongly represented among all innovative activities in ICT in these countries, signalling that an improvement of the innovative capabilities and the establishment of a reliable science landscape are central issues pursued under FP8. Moreover, also some subfields of Societal Challenges count a lot in overall innovative activities in ICT, and a relatively large amount of resources goes into RDI-projects in secure, clean and efficient energy and Europe in a changing world – inclusive, innovative and reflective societies.

Different from these similarities in the new member states, human and financial resources dedicated to projects in Industrial Leadership are much more important in the large, old member states of the EU. Especially the subfields cross-cutting activities, content technologies and information management as well as the future internet account for many actors and receive comparatively high funding from the EU. A similar picture emerges for the small, high-income member states and some associated countries. Interestingly, what we also observe with regard to the geographical distribution of resources, and what holds for more or less each country included in our sample, is that there are just two or three subfields that are outstandingly important, whilst others are relatively inferior, indicating a high degree of specialisation in RDI-efforts under this common European framework.

### 4.3. Disparities in the cross-country collaborative RDI-efforts

While our analysis has shown considerable disparities in the distribution of resources for RDI-activities in ICT across geography, these findings tell little about potential disparities existing in the
collaborative structure of RDI-activities. To enrich the picture, we focus on this second dimension in the next part of our analysis. Node-specific topological characteristics of cross-country collaboration networks provide insights into another determinant of countries’ position of power – the capability to use resources for knowledge generation in ICT under FP8.

The basis for constructing our networks of cross-country RDI-efforts in ICT is an edge-weighted directed graph: A directed graph \( G \) is a tuple \( (V, E) \), where \( V \) is the set of vertices (i.e. nodes) and \( E \) is the set of edges, containing the links between vertices. To assign weights to edges, there exists a weight function \( w: E \to \mathbb{R}_+ \). In the context of this paper, the set of vertices \( V \) is equivalent to the set of countries \( C \), while edges are determined in the following way: an edge \( e \) has the source node \( i \) and the target node \( j \) iff in an RDI-project included in our dataset there is an actor from country \( i \) who coordinates a participant from country \( j \), with \( i, j = 1, \ldots, C \). For each such connection between a coordinator from country \( i \) and a participant from \( j \) the edge weight \( w \) increases by one. By constructing our network in this way, each multi-participant action with no more than one actor from the same country is represented by an out-tree and single-participant actions (and linkages between a coordinator and a participant from the same country) as self-loops. Through this representation of networks, we retain relevant information from project-consortia, viz. the function of actors in the respective RDI-project (coordinator vs. participant). On the aggregate country level, we then obtain for each pillar \( p \) of Horizon 2020 with \( p = I, II, III \), a square and non-symmetric edge-weighted adjacency matrix \( W_p \) of dimension \( C \times C \). Based on these adjacency matrices, we calculate two global network metrics (density and connectedness) as well as three centrality metrics (degree, strength and eigenvector centrality).

Starting with a few distinct features of the skeleton of our networks, the size of the aggregate network is composed of 35 nodes (i.e. countries) and has 742 (unweighted, directed) edges including self-loops, and, there is considerable variation in the size of the pillar-specific RDI-networks (see Table 3, second column and second row as well as Figure 3, Panel (a)-(c)). Altogether, there are 14,535 actors engaged in cross-country collaborations of the aggregate network, including both coordinators and participants. On top of that, single-participant actions and multi-participant actions with more than one actor from the same country account for 4,432 self-loops. This high number of self-loops is not very surprising, and it can be attributed to the subfield small- and medium-sized enterprise instrument under pillar II, where funding rules limit the size of RDI-projects to one actor only. Focusing on network density, defined by the ratio of the actual to the maximum number of unweighted edges, this for the aggregate network is 0.642 and it increases in the size of the pillar-specific networks (see also Table 3). To figure out the extent to which ‘tightly connected neighbourhoods’ are present in the networks, we calculated a clustering coefficient. Following Fagiolo (2007), this clustering coefficient counts the actual number of triangles formed by a node and compares it to the maximum number of possible triangles it can engage in, ignoring self-loops. The ‘global’ pendant of the clustering coefficient is simply the average of the node-specific ones. Generally, the clustering coefficient lies between 0 and 1 and for the aggregate network reaches a level of 0.805. In the three pillar-specific networks, the extent of engaging in smaller communities in performing innovative activities varies only slightly. High levels of the clustering coefficients for each pillar

|                  | Aggregate Network | Pillar I: Excellent Science | Pillar II: Industrial Leadership | Pillar III: Societal Challenges |
|------------------|-------------------|----------------------------|-------------------------------|-------------------------------|
| No. of nodes     | 35                | 35                         | 35                            | 35                            |
| No. of edges     | 742               | 388                        | 582                           | 536                           |
| (incl. self-loops)|                   |                            |                               |                               |
| Density          | 0.624             | 0.326                      | 0.489                         | 0.45                          |
| (incl. self-loops)|                   |                            |                               |                               |
| Clustering coeff. | 0.805             | 0.785                      | 0.789                         | 0.746                         |

Authors’ calculations.
indicate hierarchies of dominance in the networks amounting to the presence of a few privileged innovative actors who perceive of outstanding innovative capabilities.

In the following, the focus is shifted to the structure of cross-country collaboration in the single networks as illustrated in Figure 3. We take a closer look at countries’ capabilities to use resources as measured by three centrality metrics. Due to the asymmetry of adjacency matrices, we have to distinguish between in- and out-degree, in- and out-strength as well as left and right eigenvector centrality (see, e.g., Barrat et al. [2004]; Newman [2004] and Benzi and Klymko [2013] for a discussion on these network centralities in context to a weighted (directed) network). We decided for applying degree, strength and eigenvector centrality because those metrics assess node-specific properties of each country in the RDI-collaboration networks. Each of the metrics is based on a different assumption of how collaboration in RDI-activities works and how knowledge ‘flows’ in a network. In order to compare levels of centrality metrics across pillars I-III, we normalised the scores on the interval between 0 and 1.

Figure 3. Policy-driven RDI-networks, Pillar I (Panel (a)), Pillar II (Panel (b)), Pillar III (Panel (c)). Note that the graph representation is based on the use of the Fruchterman-Reingold algorithm (see Fruchterman and Reingold 1991). Furthermore, the size and colour of nodes are determined by total degree (sum of in- and out-going edges) and the opacity and colour of edges are determined by the edge-weight. The networks have been drawn with the freeware Excel-package NodeXL. Authors’ illustrations.
• **Degree centrality:** Ignoring edge-weights, for in- (out-)degree centrality of each country we count the total number of in-coming (out-going) ties to adjacent nodes. We use degree centrality for exploring the existence of cross-country collaborative ties. Taking a closer look at the size of nodes in Figure 3, which shows for each country the total degree, we observe relatively similar degree centrality scores for a bulk of countries across the three pillars: besides the large, old EU-member states, this also includes some small middle- and high-income countries, mostly also old EU-member states, like Austria, the Netherlands, Finland and Sweden, and most notably, Greece. At the lower end of the ranking based on degree centrality, some new, middle- and low-income EU-member states can be found that seem to be only weekly integrated into collaborative European RDI-efforts under the respective pillar. Still, compared to the distribution of the available stock of both financial and human resources across geography, disparities, as measured by the Gini-coefficients for total degree centrality in each network, are at a fairly low level, indicating that there are no isolated countries. Indeed, each country has at least one incoming tie, thus participates in a project-consortium, while not all host a coordinator, signalling that there exist knowledge hubs in the networks that occupy this powerful function rather frequently (see Table 5).

• Accounting for both the number and intensity of collaborative ties, **strength centrality** is the generalisation of degree centrality to weighted networks. Normalised strength centrality scatter plots are found in Figure A1, Panel (a)–(c). These diagrams reveal a strong correlation between in- and out-strength centrality scores for each pillar, showing that the power status of countries is equally determined by the intensity of cross-country interaction of its actors in both their ability to act as coordinators and as participants. From an economic perspective, strength centrality indicates a specific form of positive externalities: The higher the intensity of collaboration between RDI-partners, the closer they are, which encourages knowledge spillovers. Compared to degree centrality, by looking at the colour and opacity of edges in Figure 3, Panel (a)–(c), one can see that for strength centrality a much more unequal distribution prevails and that only a small group of powerful countries share strong linkages, whereas most countries have rather low strength centrality scores. As shown in Table 4, the top-5 cross-country ties in terms of intensity of cooperation involve for each pillar I–III only the large member states of the EU-15 as well as the Netherlands.

Hence, not only across the geographical but also across the network dimension, disparities in knowledge generation in ICT manifest in country size (see also the Gini-coefficients in Table 5). Taken together with results of degree centrality, this implies that while it is possible to participate in the respective networks, only a few countries have the ability to engage in strong cooperative innovative activities in ICT with actors from other countries. Furthermore, despite of a high correlation between in- and out-strength centrality, actors from some of the small, high-income countries, e.g. Belgium, Austria, the Netherlands and Finland are relatively more powerful in coordinating RDI-efforts than in participating. On the other hand, there are some of the low- and middle-income new member states that do hardly or even not at all host actors who coordinate others. This effect specifically manifests in **Excellent Science** and **Societal Challenges** and hence, disparities under these two pillars as measured by the respective Gini-coefficients for out-strength centrality are higher compared to pillar II. A reason for this may be that actors from the EU-15 already possess of the required experience to engage in this comparatively more responsible role. Noteworthy, under pillar III, in-

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**Table 4.** Five most intense cross-country collaborative ties in each network.

| Intensity (in descending order) | Aggregate Network | Pillar I: Excellent Science | Pillar II: Industrial Leadership | Pillar III: Societal Challenges |
|---------------------------------|-------------------|-----------------------------|---------------------------------|-----------------------------|
| 1                               | ES → DE           | NL → UK                     | ES → DE                         | ES → IT                     |
| 2                               | ES → IT           | FR → DE                     | ES → IT                         | ES → UK                     |
| 3                               | ES → UK           | NL → DE                     | ES → UK                         | ES → DE                     |
| 4                               | ES → FR           | IT → UK                     | DE → UK                         | IT → ES                     |
| 5                               | IT → UK           | IT → DE                     | DE → FR                         | IT → UK                     |

Note that the first country acronym denotes the source node and the second one the target node. Edges are ranked in descending order, with 1 = highest intensity and 5 = lowest intensity.
strength centrality scores account for the lowest disparities, supporting our previous finding of a more inclusive structure of collaborative RDI-efforts in project consortia of Societal Challenges.

- Turning to eigenvector centrality, this metric formalises the idea that the status of a node in a network does not only depend on the number and intensity of its collaborative ties, but also on the status of its adjacent nodes, taking thereby account of the whole network structure. For a weighted and directed network, eigenvector centrality is an extension of in- and out-strength centrality, determined by the left and right eigenvector corresponding to the dominant eigenvalue. As is the case for in- and out-strength centrality, we observe a high correlation between left and right eigenvector centrality scores (see Figure A2, Panel (a)–(c)). While again the large, old middle- and high-income EU-member states (Germany, Italy, France, Spain and the UK) are the most powerful ones under each pillar, there are some countries (smaller, both new and old member states and associated countries, e.g. Austria, Finland, Ireland, Norway, Estonia, Hungary etc.) for which cooperation with those powerful countries improves their power status for right eigenvector centrality relative to out-strength, while this effect is to a lesser extent observable for left-eigenvector centrality, respectively in-strength. There are thus some ‘fellow-runners’ in the aggregate network that benefit in their capability to use resources through being connected to the frontrunners in RDI-efforts. In this way, cross-country disparities are counterbalanced slightly, which is confirmed by the Gini-coefficients for left- and right-eigenvector centrality (see Table 5).

Given the disparities that we observe along the network dimension, we further explore the distribution of organisational types that account for collaborative efforts in the networks. As illustrated in Figure 4, for both pillars II and III the most common organisational type in RDI-projects are private for-profit entities (PRC). For pillar I, on the other hand, higher or secondary education establishments (HES) is the organisational type most frequently engaged in RDI-activities, while research organisations (REC) are the second most important. Across all pillars, public bodies (PUB), which are either organisations established as a legal entity by national law or international organisations, as well as ‘other actors’ (OTH) are of lesser importance in the process of knowledge generation of ICT under FP8. This distribution does not manifest itself in specific country characteristics. Rather, it reflects the topics of calls that are prioritised under each pillar as well as the nature of actors, respectively their equipment required for performing innovative activities specific to these pillars and subfields.

In a final step, we turn to the question of whether knowledge hubs exist, in terms of actors that are, compared to others, quite often involved in project consortia dedicated to ICT. Taking a closer look at the distribution of actors that determine the power status of countries in the specific networks, out of the 14,535 actors involved in cross-country collaborations (including both coordinators and participants), 8,218 actors are engaged in at least two RDI-project consortia. This indicates that an institutionalisation of this funding mechanism has taken place within certain organisations and experience in EU-funded research plays a role in innovative activities in ICT. This effect is most pronounced for pillar I, where almost 60% of actors are involved in more than one project, followed by pillar II (50%) and, finally, pillar III (36%). Despite this uneven distribution of power, one has to keep in mind that under pillar I HES are the most common organisational type, but these usually have a much more fine-grained internal structure than accounted for under the adopted classification. In other words, if a single HES-organisation is involved in many projects, this may represent de facto very different actors, e.g. different faculties or...
institutional departments from one university. Among those organisations that are involved in at least two project consortia, the top-5 in terms of the frequency of participation in the aggregate network are mostly REC. Under pillar I, these knowledge hubs account for more than 7% of all actors involved in cross-country RDI-efforts, and for 4.8% and 3.5% of all actors for pillar II and pillar III, respectively. These knowledge hubs do not necessarily lie within the most powerful countries – the old, large, middle- and high-income EU-member states – but they can be found in associated countries like Switzerland, too. On top of that, they are also located in Greece, Finland, and Belgium. The observed scale effect gets thus slightly counterbalanced at the actors’ level, in the sense that the small, old member states have also some strong organisations that act as important loci of knowledge generation in specific niches of ICT.

4.4. Power-law behaviour in the policy-driven RDI-networks

Given our findings of significant disparities in knowledge generation existing both across the geographical and the network dimension and of such an uneven distribution of power between countries, we hypothesise that our data follows a non-normal, power-law distribution. To test for this, we perform some further statistical analysis and take total strength centrality (the sum of in- and out-strength centrality) as our test statistic. Beforehand, we have to account for the scale effect and therefore calculate total strength centrality per person employed in science and technology. To assure comparability across pillars, for each network we normalise total strength centrality of each country by the sum of total strength centralities over all countries. We then look at the empirical cumulative distribution function of the data and perform some exploratory data analysis. As can be seen from Figure 5, Panel (a)–(c), showing the histograms of normalised total strength centrality for each pillar I, II and III, data are heavily right-skewed and as data are rather strongly peaked, we also have excess kurtosis for each pillar.

To check in the next step for a non-normal, power-law distribution, we perform some statistical testing: As our sample size is rather small, the Shapiro–Wilk test is appropriate (though we also apply the Kolmogorov–Smirnov test as a robustness check that has a lower power as the former). As illustrated in Table 6, for each pillar and in either case, test results show that the null-hypothesis – i.e. data is normally distributed – can be rejected.

Given the finding that total strength centrality is not normally distributed for each pillar I, II and III, we next fit the empirical data to a power-law distribution. In the literature exist several different approaches for parameter estimation, like linear-regression based estimation, Bayesian estimation or maximum-likelihood estimation, but for our small data sample we decided to apply a graphical
fitting approach based on linear regression (see, e.g., Clauset, Shalizi, and Newman [2009] for a detailed overview on the different fitting techniques). This involves the following steps: To probe first of all, whether our data follows a power-law distribution, we plotted the cumulative empirical distribution function on a log–log scale and as this resulted in almost a straight line, this is the case. We decided to use the empirical cumulative distribution function as the basis for the analysis, as Clauset, Shalizi, and Newman (2009) have shown that this leads to comparatively accurate results. Next, we estimated the exponent of the power-law distribution, using for the linear regression the first five points of the log–log plot of the empirical cumulative distribution function. Different to using the complete data set or logarithmically binned data for the regression, according to Goldstein, Morris, and Yen (2004) this generally produces a smaller bias error, though variance and mean are relatively higher. As can be seen from Table 7, for each pillar we found a high goodness of fit as determined by $R^2$ and each of the linear regressions is significant. Parameter estimations of the linear regression $y = \alpha + \beta x$ are given in the second and third row of Table 7, where the independent variable corresponds to

Table 6. Shapiro-Wilk test for total strength centrality.

| Pillar | Test statistic | Degrees of freedom | p-value |
|--------|----------------|--------------------|---------|
| I      | 0.808          | 34                 | 0.013   |
| II     | 0.852          | 34                 | 0.031   |
| III    | 0.805          | 34                 | 0.002   |

Authors’ calculations.

Figure 5. Histograms of the empirical distribution function of normalised total strength centrality. The number of bins was defined on the basis of the rule of square roots, whereby the number of bins equals the square root of the number of observations. Note that Panel (a) shows the histogram for Pillar I (skewness = 2.101 and excess kurtosis = 5.809), Panel (b) for Pillar II (skewness = 1.565 and excess kurtosis = 3.068) and Panel (c) for Pillar III (skewness = 1.385 and excess kurtosis = 1.028). The histograms have been drawn in SPSS. Authors’ illustrations.
the logarithmic data of normalised scale-free total strength centrality and accordingly, the dependent variable are the respective cumulative relative frequencies. The exponent of the power-law distribution of some variable \( x, p(x) \sim x^{-k} \) where \( k \) is a constant, of each of our pillars is then \( 1 + \hat{\beta} \).

Based on total strength centrality, as one metric describing the collaborative structure of the networks, the presence of a power-law distribution for each pillar validates strong hierarchical patterns in the RDI-collaboration networks that, if getting persistent over time, involve the formation of an oligarchic core in knowledge generation in ICT and fortify the dominance of a few currently leading innovative actors under FP8.

5. Discussion and concluding remarks

This paper aimed at the study of disparities in innovative activities in the key technology field of ICT under Horizon 2020 across the geographical and the network dimension. We relate the analysis to two aspects of power as introduced by Boudon and Bourricaud (1989) and looked at the distribution of power among EU-member states and some countries associated with FP8. A bottom-up, actor-oriented, and linkage-based framework using statistical and network analysis has been applied.

What we find in our empirical investigation is that across both dimensions considerable disparities are evident. These come to the fore in country size and per capita income and also in the member status of countries in the EU. The remaining country characteristic – the funding intensity under the ESIF – seems not to be linked to countries’ performance in ICT-related project consortia under Horizon 2020. Concerning the old, large, middle- and high-income EU-member states of the EU (Italy, Spain, Germany, France and the UK), their dominance is straightforward and also confirmed by other research, such as Balland, Boschma, and Ravet (2019). These key players are rather similar in terms of the funding they achieve to attract, the number of actors involved in project consortia as well as their participation in cross-country collaborative RDI-efforts in ICT. One has to keep in mind, however, that their national innovation systems are less homogeneous with regard to innovative activities in ICT than they appear under this common European funding instrument. For example, Italy, Germany, France and the UK are ranked among the top-5 in the EU for the level of national business R&D expenditure in ICT and R&D personnel employed, which is not the case for Spain (cf. DESI-Report 2019). In other words, if taking account of complementary national funding tools and programmes for innovation in ICT, this may modify the power status of these key players vis-à-vis other countries, though in general, a high complementarity prevails between FP8 funding and national financial policy instruments, as Enger and Castellacci (2016) point out. Our findings thus demonstrate that innovative activities cluster in the large, old middle- and high-income EU member states where the innovation systems are sufficiently equipped to conduct such comparatively elaborate RDI-projects and the infrastructure necessary for knowledge generation in ICT is available, which is confirmed by the DESI-Report (2019) too.

On the other hand, it is surprising that the new member states are still lagging that much behind after many years of participation in the European framework programmes for research and innovation. Even if Scherngell and Lata (2011) have shown that the bundling of resources within the scope of the FPs increased between 1999 and 2006 and assess that long geographical distances impede less and less on collaborative RDI-efforts under this framework, more than 10 years later for the specific case of ICT we discern significant disparities in joint knowledge generation between these two groups of countries. Our finding is in line with Amoroso, Coad, and Grassano

| Table 7. Parameter estimation – linear regression parameters. |
|-------------------|-------------------|-------------------|
| **Pillar I:** Excellent Science | **Pillar II:** Industrial Leadership | **Pillar III:** Societal Challenges |
| \( R^2 \) | 0.9048 | 0.8642 | 0.9884 |
| \( \hat{\alpha} \) | 0.1441 | 0.8804 | 1.1633 |
| \( \hat{\beta} \) | 0.5479 | 0.8439 | 0.9489 |

Authors’ calculations.
(2017) and there are several plausible reasons for this situation of strong imbalances in the distribution of power between the EU-15 and the EU-13: For instance, innovation systems of the EU-13 may not have the critical size, infrastructure and capacity. Deciding not to apply for funding under FP8 may inter alia reflect self-selection – innovative actors in these countries simply do not have the appropriate resources to manage such project proposals and transaction costs are too high to try to get access to funding. Apart from this capacity and infrastructure failure, a lack of (access to) experienced actors may discourage participation in project consortia as well. The existence of these failures is confirmed by the EC (2017b, 92), where according to stakeholder opinions low research and innovation capabilities go hand in hand with low participation rates of the new member states under FP8. Further reasons for not participating are potential socioeconomic differences, like language barriers or simply indicate the existence of information asymmetries.

The uneven distribution of power between countries also became evident in the fact that across all three pillars there are knowledge hubs, defined as actors who participate very often and in many project consortia at the same time. It is further reflected in the intensity of collaborative ties and hence in the capability to use resources for innovative activities, as very intense and strong collaborative ties are almost exclusively tied to actors from the large, old member states. As we have pointed out, the way in which we constructed our networks – as (weighted) directed graphs – allows accounting for the different roles adopted by innovative actors in project consortia. In this way, we produced another interesting result: The role of the coordinator in a project consortium frequently is occupied by actors from old EU-member states – though not necessarily the large ones but rather those with high per capita income. The presence of such strong hierarchical patterns between innovative actors from different countries is confirmed by Wanzenböck, Scherngell, and Lata (2015) for RDI-collaboration in ICT under the European FPs between 1998 and 2006.

On the whole, the unequal distribution of power complies with the credo of funding rules of Horizon 2020 (‘excellence, impact, and quality and efficiency of implementation’). Nevertheless, we consider this situation as obstructive for the Europeanisation of innovation, as the full innovative potential across the European Union and associated countries cannot be exploited if only a few privileged actors have access to funding and the capability to use resources for innovative activities is limited. Turning to the policy implications of our study, we think that establishing a more cohesive, egalitarian European knowledge base is an essential step for future innovation policy in the EU. This is all the more important since ICT is a generic technology field that disposes of a wide application field and carries high transformative capacities. Policy measures aiming at the reduction of existing disparities need to consider the following: First, the degree of inclusion should be increased and the existing heterogeneities between actors of the European Union (and the associated countries) ought to be taken advantage of. If successful, this stimulates technological capabilities across the EU. However, strong commitment from national governments is required to set incentives for participation in EU RDI-efforts and direct the different types of actors towards investing in innovation in the technologies that mark the digital transformation. Horizon 2020 terminates in less than a year and it is necessary to prevent such segregation in the access to funding under future FPs. To achieve this, the appropriate mechanism and incentives have to be set, which could include: first, fostering the participation of actors from less powerful countries to a larger extent than is currently the case. In principle, there exist FP8-actions that should serve that purpose – the so-called ‘spreading excellence and widening participation’ actions. As Ukrainski et al. (2018) point out, these, however, lack effectiveness and currently cannot unfold their full potential. Second, to prioritise the coupling of the FPs with a policy instrument explicitly targeting cohesion, viz. ESIF, in order to create synergies. Third, apart from stimulating networking and closer cooperation between actors from different countries, it might be equally helpful to implement less formal cooperation mechanisms which, for instance, encourage the sharing of skills and competences across borders and foster the mobility of innovative actors.

We consider it worth conducting further research in three directions: On the one side, we focused on a time-static framework. To study how the distribution of power evolves and whether there is persistence in the oligarchic patterns we identified, a time-dependent approach is required. We think
that this is interesting, as ICT has already been included in previous EU framework programmes for research and innovation and data is hence available. Another idea that seems promising is to explore different types of networks based on patenting activities or other collaboration mechanisms in innovative activities. It would permit a more fine-grained analysis of the different stages of innovation in ICT. Finally, an extension of our research to incorporate also national funding instruments for RDI-projects in ICT could be fruitful, as it provides a full-fledged picture on the distribution of power in innovative activities in this key technology field.

Notes
1. These are: (1) the innovation union, (2), youth on the move, (3) a digital agenda for Europe, (4) resource-efficient Europe, (5) an industrial policy for the globalisation era, (6) an agenda for new skills and jobs, (7) European platform against poverty. ICT is prioritised under (1), (2), (3), (6), and (7).
2. See CORDIS Open Data Portal (EU 2012) for a definition and detailed explanation of the variables included within the basic files.

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### Appendix

| Abbreviation | Country name     | Population size | Country size | Income group | Funding intensity under ESIF |
|--------------|------------------|-----------------|--------------|--------------|-----------------------------|
| AT           | Austria          | 8,640,701       | small        | high         | low                         |
| BE           | Belgium          | 11,277,137      | small        | high         | n.a.                        |
| BG           | Bulgaria         | 7,176,584       | small        | low          | low                         |
| CH           | Switzerland      | 8,281,048       | small        | high         | n.a.                        |
| CY           | Cyprus           | 1,161,140       | small        | middle       | low                         |
| CZ           | Czech Republic   | 10,544,346      | small        | low          | high                        |
| DE           | Germany          | 81,778,932      | large        | high         | low                         |
| DK           | Denmark          | 5,686,025       | small        | high         | n.a.                        |
| EE           | Estonia          | 1,315,478       | small        | low          | low                         |
| EL           | Greece           | 10,820,012      | small        | low          | medium                      |
| ES           | Spain            | 46,457,513      | large        | middle       | high                        |
| FI           | Finland          | 5,478,713       | small        | high         | low                         |
| FR           | France           | 66,617,378      | large        | middle       | n.a.                        |
| HR           | Croatia          | 4,204,198       | small        | low          | medium                      |
| HU           | Hungary          | 9,842,485       | small        | low          | medium                      |
| IE           | Ireland          | 4,689,052       | small        | high         | low                         |
| IL           | Israel           | 8,380,967       | small        | middle       | n.a.                        |
| IS           | Iceland          | 330,818         | small        | high         | n.a.                        |
| IT           | Italy            | 60,706,771      | large        | middle       | high                        |
| LT           | Lithuania        | 2,903,192       | small        | low          | low                         |
| LU           | Luxembourg       | 569,632         | small        | high         | n.a.                        |
| LV           | Latvia           | 1,977,244       | small        | low          | low                         |
| MT           | Malta            | 432,062         | small        | middle       | low                         |
| NL           | Netherlands      | 16,941,113      | small        | high         | n.a.                        |
| NO           | Norway           | 5,186,256       | small        | high         | n.a.                        |
| PL           | Poland           | 37,982,054      | large        | low          | high                        |
| PT           | Portugal         | 10,361,250      | small        | middle       | low                         |
| RO           | Romania          | 19,809,920      | small        | low          | high                        |
| RS           | Republic of Serbia | 7,094,457   | small        | low          | n.a.                        |
| SE           | Sweden           | 9,799,473       | small        | high         | medium                      |
| SI           | Slovenia         | 2,063,452       | small        | middle       | low                         |
| SK           | Slovakia         | 5,423,718       | small        | low          | high                        |
| TR           | Turkey           | 78,271,509      | large        | low          | n.a.                        |
| UK           | United Kingdom   | 65,126,420      | large        | low          | low                         |

Note that in the 6th column ‘n.a.’ stands for ‘not available’.
Figure A1. Normalised strength centrality distribution, Panel (a): Pillar I, Panel (b): Pillar II, Panel (c): Pillar III. Authors’ illustrations.
Figure A2. Normalised eigenvector centrality distribution, Panel (a): Pillar I, Panel (b): Pillar II, Panel (c): Pillar III. Authors’ illustrations.