PARIS REINFORCE

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D3.4 STAKEHOLDER COUNCIL MAPPING

WP3 – Ongoing stakeholder dialogue

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EC Summary Requirements

1. Changes with respect to the DoA

No changes with respect to the work described in the DoA. The deliverable was submitted on time (May 31, 2020), and then revised in September 2020 with a complementary network analysis of stakeholders, additional to contractual commitments. It is noteworthy that the innovation dynamics that we had aimed to capture are in part reflected in the enhanced stakeholder database; part of that ambition was unattainable due to the COVID situation, which did not allow us to properly follow up with our stakeholders, and not all required information could be captured via the enhancement approach followed to fill in the gaps.

2. Dissemination and uptake

This deliverable describes the process and outcomes of the mapping process of the PARIS REINFORCE Stakeholder Council. As no personal information of stakeholders is disclosed, its dissemination level is public. The deliverable can be used as a reference document for all interested parties to evaluate the coverage of the stakeholder pool engaged in PARIS REINFORCE.

3. Short summary of results (<250 words)

We develop a mapping for the PARIS REINFORCE Stakeholder Council, which is essential for the co-creation process enshrined in the project's objectives. The aim is to enable stakeholder interaction and ensure inclusivity of the Council.

Starting from the Stakeholder Council database, we enhance it and analyse the nature of the Council by mapping the geographic location and sector of activity of its members. Efficiency is enhanced by gaining information on the different stakeholders, allowing to quickly identify relevant actors, and to gain awareness on their interests. This enhanced mapping also improves inclusiveness, as it allows the identification of potential gaps in the Stakeholder Council coverage, of geographic and sectoral nature.

To obtain information on the geographic location and type of stakeholder present in the database, we use innovative database enhancement techniques. We start by evaluating the information at our disposal and its characteristics. We then develop a strategy to increase the available information, applying automated search methods on Google and Wikipedia to the database.

We then enhance the resulting expanded database using natural language processing techniques, by assigning a geographic location, category, and sector to each entry. In a second stage, we analyse the resulting enhanced database to provide insights into the coverage of the Stakeholder Council database.

The analysis and enhancement of the Stakeholder Council database is complemented by a network study aiming to gain insights into the structure of online interactions between climate-economy modelers and policymakers; and to identify key actors in linking climate-economy modellers and policymakers. This study is performed on the broader climate change community.

4. Evidence of accomplishment

This report.

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Preface

PARIS REINFORCE will develop a novel, demand-driven, IAM-oriented assessment framework for effectively supporting the design and assessment of climate policies in the European Union as well as in other major emitters and selected less emitting countries, in respect to the Paris Agreement. By engaging policymakers and scientists/modellers, PARIS REINFORCE will create the open-access and transparent data exchange platform I^{2}AM PARIS, in order to support the effective implementation of Nationally Determined Contributions, the preparation of future action pledges, the development of 2050 decarbonisation strategies, and the reinforcement of the 2023 Global Stocktake. Finally, PARIS REINFORCE will introduce innovative integrative processes, in which IAMs are further coupled with well-established methodological frameworks, in order to improve the robustness of modelling outcomes against different types of uncertainties.

NTUA - National Technical University of Athens	GR
BC3 - Basque Centre for Climate Change	ES
Bruegel - Bruegel AISBL	BE
Cambridge - University of Cambridge	UK
CICERO - Cicero Senter Klimaforskning Stiftelse	NO
CMCC - Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici	IT
E4SMA - Energy Engineering Economic Environment Systems Modeling and Analysis	IT
EPFL - École polytechnique fédérale de Lausanne	CH
Fraunhofer ISI - Fraunhofer Institute for Systems and Innovation Research	DE
Grantham - Imperial College of Science Technology and Medicine - Grantham Institute	UK
HOLISTIC - Holistic P.C.	GR
IEECP - Institute for European Energy and Climate Policy Stichting	NL
SEURECO - Société Européenne d'Economie SARL	FR
CDS/UnB - Centre for Sustainable Development of the University of Brasilia	BR
CUP - China University of Petroleum-Beijing	CN
IEF-RAS - Institute of Economic Forecasting – Russian Academy of Sciences	RU
IGES - Institute for Global Environmental Strategies	JP
TERI - The Energy and Resources Institute	IN

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Executive Summary

In this document we develop a mapping for the Stakeholder Council of the PARIS REINFORCE project. The aim of this mapping is to enable stakeholder interaction and to ensure the inclusivity of the Stakeholder Council. The PARIS REINFORCE Stakeholder Council is essential for the co-creation process enshrined in the project's objectives.

Starting from the Stakeholder Council database, we enhance it and analyse the nature of the Council by mapping the geographic location and sector of activity of its members. Efficiency is enhanced by gaining information on the different stakeholders, allowing to quickly identify relevant actors, when needed, and to gain awareness on their interests as well. This enhanced mapping also improves inclusiveness, as it allows the identification of potential gaps in the Stakeholder Council coverage, of geographic and sectoral nature.

To obtain information on the geographic location and type of stakeholder present in the database, we use innovative database enhancement techniques. We start by evaluating the information at our disposal and its characteristics. We then develop a strategy to increase the available information using automated search methods on Google and Wikipedia applied to the Stakeholder Council database.

In turn, we enhance the resulting expanded database using natural language processing (NLP) techniques, by assigning a geographic location, category, and sector to each entry. In a second stage, we analyse the resulting enhanced database to provide insights into the coverage of the Stakeholder Council database.

The analysis and enhancement of the Stakeholder Council database is complemented by a network study aiming to gain insights into the structure of online and offline interactions between experts and policymakers. It will allow to identify key actors in linking climate-economy modellers and policymakers. In order to facilitate a sensible analysis and improve data quality, the sample considered for these studies is not the same sample that PARIS REINFORCE records in the Stakeholder Database. In fact, the results of this analysis have the potential to contribute toward a productive expansion of the Stakeholder Database.

In addition, methodological approaches mean that the categorisation of stakeholders differs from that in the Stakeholder Database to the online and offline analyses. However, the network analyses are characterised by a fundamental focus on interactions with policymakers providing useful insights for the progress and future of the project's engagement with key stakeholders.

The main findings obtained from this section are that in online interactions different types of stakeholders tend to communicate with their own kind. Also, the natural communities detected in the Twitter networks reflect geographies rather than stakeholder categories, indicating that it is in that area that bridges must be created. Finally, at the moment, the links between these geographical communities are mostly formed by experts, who appear to interact with actors form all communities, while policymakers stay more isolated.

Regarding offline interactions, for which we consider the participants of climate- and energy-related events, we notice that DGs are not as well connected as one would expect. Also, we find that speakers that connect DGs/ institutions can be classified in three broad communities, global diplomatic, global technical and local technical actors. Furthermore, given that we focus on the policy sphere we find this time around that policymakers play the most central role in the offline network.

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1 Introduction

The PARIS REINFORCE Stakeholder Council is essential for the co-creation process enshrined in the project's objectives. It aims to be the bedrock of knowledge representing the expertise, interests, motives, and strategies of all relevant actors in respect to the broader spectrum of transformations required for decarbonisation and will operate throughout the project's lifetime. The Stakeholder Council will be mobilised for the purposes of sharing ideas, skills, and experience in all scientific processes of the project, including all stages of modelling. Through bilateral (semi-structured interviews, phone calls, face-to-face meetings, questionnaires) and multilateral (online meetings, webinars, surveys, and physical workshops) communication, the Stakeholder Council will pose the key policy and research questions, and provide the consortium with input data (preferences, expertise, scenario parameters, etc.) and feedback, so as to ensure high quality and policy and science relevance. **These defined methods of communication and interaction have been subject to change according to the implications of the ongoing COVID-19 crisis.** Members of the Stakeholder Council will also be the first to be invited to attend PARIS REINFORCE events and workshops as well as to have access to news, publications, pre-final drafts and briefs. To reap the full benefits of the Stakeholder Council, it is important to understand its composition and identify gaps in its coverage.

Having defined the scope of the PARIS REINFORCE Stakeholder Council and the manner in which the consortium will engage with it in the Stakeholder Engagement Plan (D3.1), the following report seeks to contribute toward facilitating an efficient and inclusive stakeholder engagement process. Starting from the Stakeholder Council database, we enhance the quality of stored data and analyse the nature of the Stakeholder Council by mapping the geographic location and sector of activity of its members. Efficiency is enhanced by gaining useful information on the different stakeholders, allowing to quickly identify relevant actors when needed and gaining awareness on their interests as well. The enhanced stakeholder mapping also improves inclusiveness, as it allows the identification of potential gaps in the Stakeholder Council coverage, in geographic and sectoral terms.

To obtain information on the geographic location and type of stakeholders present in the database, we use innovative database enhancement techniques. We start by evaluating the information at our disposal and its characteristics. This process allows us to uncover opportunities and limitations of the initial dataset at hand. Then, we develop a strategy to increase the available information using automated search methods on Google and Wikipedia applied to the Stakeholder Council database. We enhance the resulting expanded database using natural language processing (NLP) techniques, by assigning a geographic location, category, and sector to each entry. In a second stage, we analyse the resulting enhanced database to provide insights into the coverage of the Stakeholder Council database. We identify gaps in the Stakeholder Council on two levels, geographically, at European and global scale, and sectorally, identifying coverage gaps in groups and subsectors.

The analysis and enhancement of the Stakeholder Council database is complemented by a network study aiming to gain insights into the structure of online interactions between climate-economy modellers and policymakers. In addition, it will allow to identify key actors in these interactions. The result of this study will enable PARIS REINFORCE to assess the level of communication between policymakers and scientists, and stimulate it by relying on key actors of the policy discussion we will have identified. The study draws from two sources of data; first, lists of participants from climate and energy policy-related events and, second, from the microblogging social network of Twitter. The former are obtained through desk research and automated input analysis, the second through the publicly accessible Twitter Application Programming Interface (API). This process is compliant with GDPR. Different methodological approaches and data availability mean that the categorisation of stakeholders differs from the Stakeholder Database to the twitter and event network analyses.

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2 Literature review

2.1 Theorical frameworks for stakeholder analysis

There exists a broad array of methods to identify and analyse stakeholders. Different approaches can be categorised under three board umbrellas: the normative approach, the instrumental approach, and the descriptive approach (Donaldson & L., 1995), (Friedman & Miles, 2006).

The first one refers to a mapping process, which focuses on the legitimacy of stakeholder involvement and empowerment in decision-making processes (Reed & Curzon, 2015). The reasoning behind the normative approach is based on the need for decision makers to take into account the well-being of those affected by their decisions, potentially due to a form of moral responsibility (Berman, Wicks, Kotha, & Jones, 1999). It then follows that systematically understanding who these stakeholders are is an essential first step in any decision-making process and requires early identification and involvement of a representative cross-section of stakeholders.

The instrumental approach focuses on understanding how stakeholders to a certain project can be identified and their behaviour be explained and managed. But the instrumental approach also focuses on how stakeholders can manage decision makers to achieve their desired outcome. Theories in this category imply that certain outcomes are more likely if decisions makers behave in certain ways towards stakeholders and vice versa (Reed & Curzon, 2015). Stakeholders are thought to affect the final outcome in two ways under the instrumental approach, either directly, by affecting the result of the process themselves, or indirectly, through a moderation role on the decision-makers (Berman, Wicks, Kotha, & Jones, 1999).

The third theoretical category of stakeholder mapping approaches is referred to as the descriptive approach. It entails the examination of how stakeholder characteristics influence the decision-making process and focuses on describing the relationship between stakeholders and decision makers (Berman, Wicks, Kotha, & Jones, 1999); (Reed & Curzon, 2015). The most important model from this category is the one developed by Mitchell et al. (1997). It states that stakeholders become significant to decision makers according to three attributes they may possess: power, legitimacy and urgency (Harrison & Freeman, 1999). Power is based on leverage or symbolic influence, which may be yielded to push the decision makers to behave in a certain way. Mitchell et al. (1997) describe legitimacy as a perception that stakeholder actions are desirable, proper, and appropriate within society's beliefs. Finally, urgency is defined as the degree to which a stakeholder's claim calls for immediate attention.

For the purpose of the PARIS REINFORCE stakeholder mapping, we will focus on the descriptive approach. We believe this method is most suited to our needs as it offers a clear way to analyse the Stakeholder Council database. A fundamental goal of the Paris Reinforce project is the development of an inclusive process of engagement with relevant stakeholders. Such a framework seeks to involve different kinds of stakeholders in different elements of the project ranging from the co-creation of policy questions to the design of web interfaces to feedback on modelling results. The developed stakeholder mapping allows for a ranking of stakeholders according to different criteria, which is useful to fulfil these stakeholder engagement purposes.

2.2 Stakeholder identification and categorisation

Stakeholder identification is usually done in two broad ways, ex-ante and ad hoc. The ex-ante identification of stakeholders is often done using secondary data sources such as through oral or written accounts of events or through census data. Ex-ante identification can also be enriched using a call for voluntary participation where stakeholders self-identify as stakeholders and seek to provide input in the process. This initial identification of stakeholders may then be used to select event participants and, from there on, start mapping stakeholders more

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systematically (Dougill, et al., 2006). The ad hoc approach is an iterative process, it involves provoking feedback from new stakeholders as they are identified and allowing them to in turn identify new stakeholders. This might be referred to as the snowball sampling approach. PARIS REINFORCE will use both approaches to stakeholder identification: first, as reflected in this report, an initial identification is conducted using secondary sources allowing to identify stakeholders to be invited to our workshops; second, stakeholders will be approached during these workshops and a more detailed classification will be done. Questions that will be asked to workshop participants include:

- How are they affected by decarbonization strategies?
- How do they impact science and policy-making towards climate targets?
- Is their impact local, national, or international?
- What is their level of interest in the PARIS REINFORCE process?

In the literature, two ways to categorise stakeholders emerge: using predefined categories or developing categories using a bottom-up process. Pre-defined categories include classifications that rank stakeholders according to levels of interest and influence (Eden & Ackermann, 1998), cooperation versus competition/threat, or urgency versus legitimacy versus influence (Mitchell, Agle, & Wood, 1997). These categorisations then, in turn, allow for adaptive interaction approaches. For instance, low interest stakeholders will be harder to involve than high interest ones and will therefore require extra effort to get on board. Bottom-up approaches are somewhat different, they rely on stakeholders categorising themselves and are therefore considered more agnostic (Reed, et al., 2009). However, these approaches may lead to overlaps and inconsistencies in the categorisation, making its practical use more limited (Reed & Curzon, 2015). The PARIS REINFORCE stakeholder mapping will rely on the predefined category approach, since it allows for more precision and is easier to implement.

2.3 Stakeholder interactions

Understanding how stakeholders interact is also of high importance and there is a range of methods that have been created to do so; these methods are sometimes also referred to as actor analysis. In the process of PARIS REINFORCE, performing such analysis is important given the need to facilitate knowledge exchange between policymakers and modellers, who may have different norms and values and preferred methods of communication. Actor analysis methods are usually performed after stakeholders have been categorised and aim to shed light on how different groups interact with one another, and to identify specific individuals or organisations that play an important role in diffusing knowledge and practises within and among stakeholder groups (Reed & Curzon, 2015).

There exists an extensive number of methods to analyse stakeholder relationships, including social network analysis (Prell, Hubacek, & Reed, 2008) (Prell, Hubacek, & Reed, 2009), knowledge mapping (Nissen & Levitt, 2004), actor linkage matrices (Biggs & Matseart, 1999), comparative cognitive mapping of social perceptions and values (Bots, van Twist, & van Duin, 2000), mind or fuzzy cognitive mapping (Kontogianni, Papageorgiou, & Tourkolias, 2012), and focus and in-depth interviews (Dougill, et al., 2006). We will use social network analysis methods since it matches best the data available to us and fits our intention to have a full data-driven approach for this part of the analysis.

According to Reed and Curzon (2015), a key challenge is to identify and tap into existing social networks, which may be able to spread knowledge, and to stimulate new exchanges and networks, where links are undeveloped (between different professional groups that do not typically interact with one another). For this purpose, the social network approach is particularly effective, as it provides a clear mapping of the interactions and allows to identify groups. In addition, social network analysis methods are effective in uncovering the role of “knowledge brokers”

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or 'intermediaries' in the diffusion of information and knowledge through networks. As such, Reeds and Curzon (2015) note that it is possible to identify individuals or groups with intermediary roles within networks using measures such as betweenness centrality. This measure assigns the highest score to a person or organisation in the network, through which the largest number of interconnections are made (largest number of shortest paths). We implement social network analysis methods in Section 4.

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3 Stakeholder Council database enhancement and analysis

3.1 Method

In this section we enhance the Stakeholder Council database using innovative data processing techniques. Starting from the initial Stakeholder Council database with limited information, we move towards an enhanced version of this same database fit for analysis and for usage as a stakeholder engagement tool.

3.1.1 Evaluation of the initial database

In line with the Stakeholder Engagement Plan (D3.1), the initial database was created by contacting potential stakeholders via email, having interested stakeholders self-reporting via a dedicated form included in the PARIS REINFORCE website and by identifying potential stakeholders by tapping into the networks of consortium members. Such an approach ensured that the stakeholders included would come from different geographies, branches of society and interest groups, **in line with the principles of the Talanoa dialogue**.

Then, the stakeholders' details were filled into a Customer Relationship Management (CRM) software tool. The variables included in the questionaire submitted to stakeholders are presented in Table 1. Some of the most important variables include: stakeholder category (e.g. government, NGO etc.), geographic area, field of activity/sector, level of activity, interest in the project, level of influence (within their level of activity), initial date of engagement, and any issues or concerns raised (Table 1).

Table 1: Response rates for different variables among stakeholders of the initial PARIS REINFORCE Council

Variable	Response rate	Variable	Response rate
GDPR consent	31%	**Mobile**	9%
First Name	100%	**Twitter**	0%
Last Name	100%	**Country**	48%
Organisation	97%	**City**	47%
Job title	46%	**Postal Code**	20%
Email	100%	**Partner Reference**	99%
Stakeholder category	44%	**Level of Activity**	4%
Field of Activity/Sector	17%	**Interest in Engagement**	1%
Salutation	36%	**Influence (within level of activity)**	18%
Phone	29%	**Notes**	8%

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The initial database is composed of 3,701 entries with highly heterogeneous degrees of completeness, ranging from 100% to 1% (Table 1). The only variables with full information are first name, last name, organisation, and email, while other key variables such as country and stakeholder category and field of activity are all less than half full. Other important variables display even lower response rates, such as level of activity, interest in engagement and influence which have response rates of 4%, 1% and 18% respectively. The low response rates pose a problem in terms of the representativeness of the sample, as only very few entries have full information.

As outlined in the Stakeholder Engagement Plan (D3.1), for the Stakeholder Council to be effective in providing inputs into the PARIS REINFORCE co-creation process, targeted interactions are needed. For instance, when organising a local workshop, one must be able to access local stakeholders from various interest groups. For such a purpose, the initial level of information in the Stakeholder Council database is too limited and therefore requires an enhancement. To maximise the outreach of the database, we focus on the variables, for which we have full information, and which can be exploited effectively. Organisation names are information-rich, as they constitute public information and can therefore be searched easily on platforms like Google and Wikipedia. Email addresses also offer useful information as their domains, in certain cases, reflect the country from which they originate. In the next sections we outline two tools we employed to increase the amount of information in the database.

3.1.2 Google Maps API

First, we use the Google places Application Programming Interface (API) to link organisation names to geographic locations and to types of organisations. This allows us to precisely pinpoint the location of each stakeholder using strictly public information. This approach is achieved by running a Python script through the list of organisations using the Python Google Maps package. As such, each organisation is searched in an automated way on Google Maps leading to the full address and type of place being returned and stored. The information obtained from this approach is the detailed geographical location of each organisation and the type of organisation according to Google's definition.

The advantages of this approach are that it allows to identify the geographic location of a very large number of entries in an efficient manner. In addition, Google's search tool cleans the data and standardises them by removing typos and alternative spellings. Finally, the locations obtained are very precise, as the search returns the city and country of each organisation but also more detailed information, such as the street name and number, thereby allowing for seamless access in the future. Nevertheless, the Google Maps API enhancement approach also has severe limitations. First, the types of locations returned by Google are very generic and broad; as such, all private establishments, excluding banks, are returned as "point of interest". It was only for schools, universities, and certain public offices that the type returned provided useful information. In addition, the Google search function is not exempt from errors, leading certain organisations to be identified incorrectly. For instance, when searching for certain energy companies, their local tank station was returned instead of their offices. Another issue is the local bias of Google searches; indeed, Google identifies the location of the search and therefore tends to select places, near which the search was originated from—in this case, Belgium. Nevertheless, this issue was partially corrected using country location information available such as the country variables and email address domains.

3.1.3 Wikipedia API

While the Google maps API approach added information to the database about the geographic location of the different stakeholders, it failed to provide insights on the category of each stakeholder and the sector in which they operate. To obtain further information, we further enhanced the Stakeholder Council database by performing an automated search on Wikipedia for all entries of the database. Wikipedia is a multilingual online encyclopedia created and maintained as an open collaboration project. It was selected as an alternative source of information

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because of its free access API and its size; indeed, it currently hosts over six million articles in English[1]. Although Wikipedia is an open collaboration project, the accuracy of its articles has been found in the past to be close to that of traditional encyclopedias (Giles, 2005).

For each entry of the database, if found, the Wikipedia summary of the organisation is retrieved, and the text is analysed to extract information from the summary. The result allows to identify whether the entry is a private sector entity, a government body, an academic institution, or an NGO and in which sub-sector it operates. The entries are first searched for a direct hit and, in a second step if no result was found in the first, through an automated search. This allows to increase the number of results but comes at the cost of accuracy in certain cases. The next step is to extract information from the retrieved summary. The NLP method used for this purpose identifies words in the summary that fall in the lexical fields of each stakeholder category. For instance, words such as "University, campus, research etc." are associated with the category academia. All the other keywords and bigrams (combination of words) are to be found in Annex 1. In this manner, for each entry, a score is calculated representing the probability of belonging to a certain stakeholder category, through which a category is assigned to the entry. Afterwards, a similar method is employed to assign a subsector and a country to each entry, this time using lexical fields associated to the different subsectors countries the entry can be categorised as.

The advantage of this approach is that it taps the large potential of Wikipedia as a source of supplementary information, giving access to detailed information about each entry. In addition, this approach allows to gather information at a large scale and low cost. There are some caveats concerning the approach. First, it is biased towards larger entities as small firms and organisations may not have a Wikipedia page. Second, it leads to some identification mistakes as the names of the organisations in the listings do not match exactly the names of the Wikipedia page of the organisation or the Wikipedia search function retrieves the wrong page. Third, there is a trade-off between precision and coverage depending on the usage of the auto-suggest function. To the extent possible, manual checks have been made at random to evaluate the validity of the approach. The conclusion has been that these caveats do not pose a significant threat to the quality of the reported date.

3.1.4 Enhanced database

In Table 2 we display the response rates of the enhanced database. The rates are now significantly higher for the variables 'stakeholder category', 'field of activity/sector', 'country', and 'address (City)'. This enhanced database is a better tool for stakeholder engagement as geographic precision is significantly enhanced and stakeholder category and sector are available for close to 90% of all entries. This information allows for targeted interaction with stakeholders as one can, for instance, easily identify an environment conservation foundation in Greece or an energy company in Denmark, both of which inputs are important for the co-creation process.

Table 2: Response rates for different variables among stakeholders of the enhanced database

Variable	Response rate	Variable	Response rate
First Name	100%	**Country**	86%
Last Name	100%	**City**	47%

[1] https://en.wikipedia.org/wiki/Wikipedia:Size_comparisons

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Organisation	97%	**Postal Code**	20%
Job title	46%	**Partner Reference**	99%
Email	100%	**Level of Activity**	4%
Stakeholder category	90%	**Interest in Engagement**	1%
Field of Activity/Sector	88%	**Influence (within level of activity)**	18%
Salutation	36%	**Notes**	8%
Phone	29%	**Address**	80%
Mobile	9%	**Google name**	79%
Twitter	0%	**Summary**	88%

3.2 Enhanced Stakeholder Council database analysis

In this section we analyse the enhanced Stakeholder Council database to find potential "stakeholder gaps" in its coverage. This identification process allows us to ensure that, for each geographical area of interest, PARIS REINFORCE engages with a sufficient number of relevant stakeholders from diverse enough backgrounds, to develop a holistic understanding of the required modelling needs. This approach is in full alignment with the essence, inclusiveness, and purpose of the Talanoa dialogue, whereby PARIS REINFORCE will engage with a group as diverse and balanced as possible (by region, nationality, institution, function, gender, etc.) that can act as an interface and multiplier in their respective country or organisation.

3.2.1 Stakeholder geographic coverage analysis

The key goals listed in table 3 are selected from the project's grant agreement performance indicators. They are considered as particularly important metrics to consider with respect to the geographic and sectoral coverage of the database. These goals can be considered as the bare minimum with which the coverage of the enhanced stakeholder database should facilitate. Given that the process of stakeholder engagement and mapping is designed to be a dynamic process, evolving over the next two years, a direct comparison of the current database with these goals is not necessarily informative.

These goals will be used on a continued basis to identify the most fundamental 'stakeholder gaps'. These gaps will not however be exhaustive. It is likely that the research and direction of the project will require expertise from particular geographic and sectoral areas as it progresses and hence efforts will be expended to expand the stakeholder database in these directions.

Table 3: Key Goals
Participation within the Stakeholder Council
More than 20 EU policymakers
More than 2 national policymakers per country for at least 12 EU countries

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More than 2 national policymakers from each considered 'less-emitting country'
More than 30 stakeholders per group
Events
More than 40 participants at each regional EU workshops
More than 20 participants in national workshops
More than 30 stakeholders per each national policy event
More than 20 participants in the Kenyan and Ukrainian stakeholder workshop
Two series of national workshops in at least ten European countries
One stakeholder workshop in six major emitting countries

Note: the list of key goals in this table are not exhaustive but selected as particularly important for this deliverable.

At the European level, climate policy support will be offered at both a regional and national level. Therefore, stakeholders at both the European regional and national level are valuable. An impact at the national level is also targeted for non-EU (but European) countries, particularly Norway, Switzerland, Ukraine, and the Balkan countries.

Outside of Europe, the project will mobilise stakeholder networks to have an impact in a set of major emitting countries: Brazil, Canada, China, India, Indonesia, Japan, Mexico, Russia and the United States of America. The project will additionally focus on a range of less-emitting countries: Kenya, the Gulf Council Countries (GCC), the Central Asian Caspian (CAC) region, Australia, and South Africa.

3.2.1.1 European coverage of the Stakeholder Council database

By evaluating the coverage of the Stakeholder Council database in Europe (Figure 1), we can make several observations regarding "stakeholder gaps" and uneven geographical distributions of stakeholders. We notice a very large concentration of the stakeholders in Western Europe, especially in Belgium. This is due to many of the stakeholders having been sourced from Bruegel's network, which is principally located in Belgium. Furthermore, the UK and France also have around 400 stakeholders each, while Germany has around 300. Conversely, although there is coverage, the number of stakeholders in the South East of Europe is limited, for instance in Romania and Bulgaria there are only 2 and 3 stakeholders, respectively. Nevertheless, thanks to the contribution of NTUA the database has a rich coverage of Greece. In the North, the Scandinavian and Baltic countries also appear to display gaps in coverage—for instance, the database does not contain any stakeholder from Lithuania. Finally, another striking stakeholder gap is to be found in the Balkans where no stakeholder is included from either Serbia, Albania, Kosovo, Montenegro, or Northern Macedonia.

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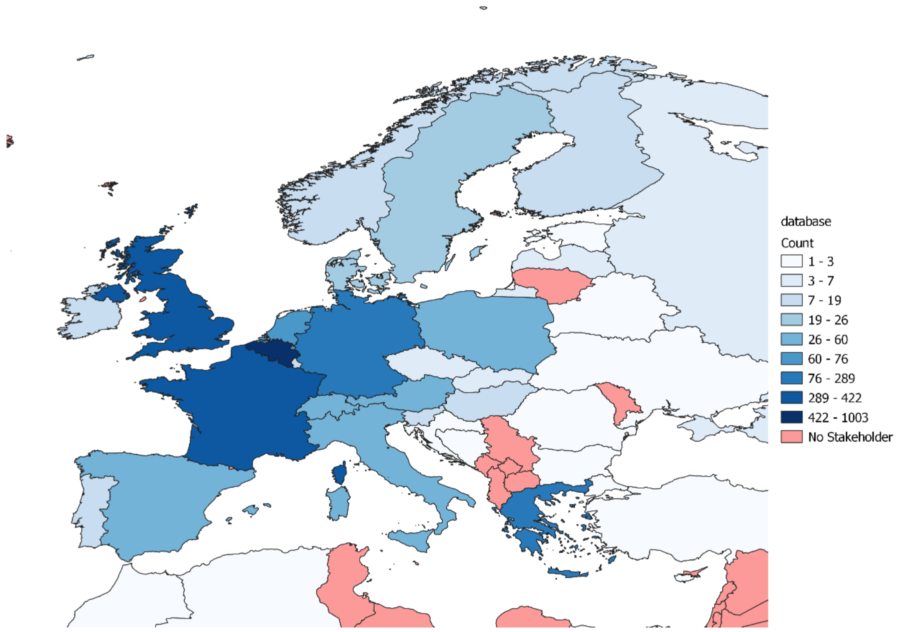

Figure 1: Regional coverage of the Stakeholder Council database in Europe

3.2.1.2 Worldwide coverage of the Stakeholder Council database

From Figure 2, we notice a broad but uneven coverage of the database globally. As expected, the coverage is the densest in Europe, but we notice that other key countries are included as well. The United States is the country outside of Europe with the largest number of stakeholders amounting to 76. The database also includes stakeholders from nearly all large emerging economies, including China, India, Russia, Brazil and South Africa, but fails to include Indonesia to achieve full coverage of all the BRICS countries. We identify six regions with no coverage, namely Central America, the Caribbean, Central Africa, Central Asia, the Middle East and South-East Asia. However, these are also the regions with the weakest model coverage from the PARIS REINFORCE modelling capacity. Notably, Southeast Asia, Central America and the Caribbean all have only one model covering them (Figure 2 D3.2).

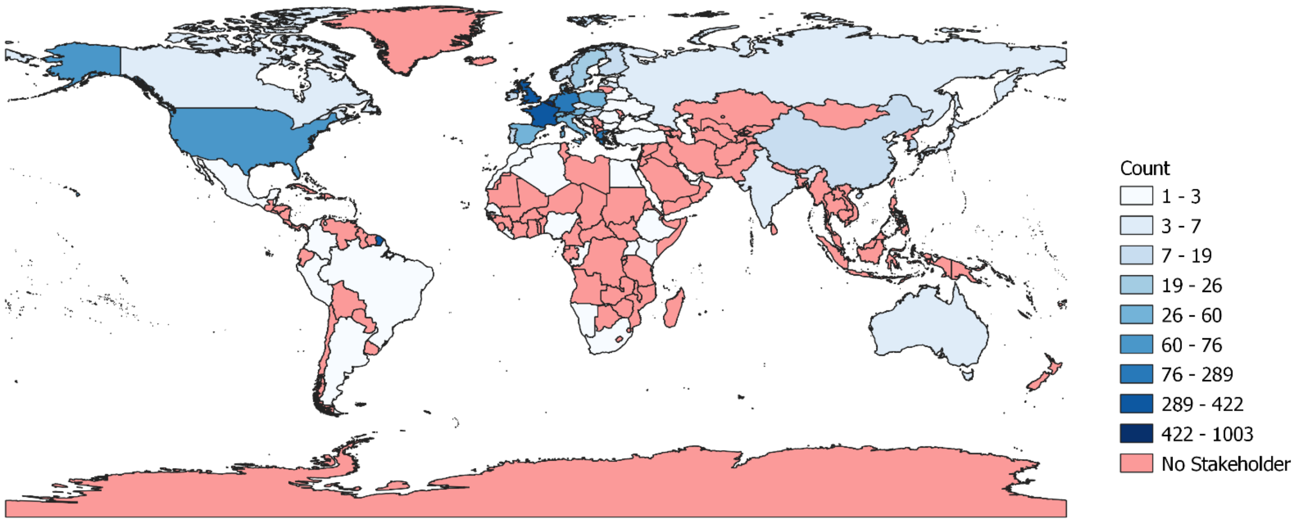

Figure 2: Worldwide coverage of the Stakeholder Council database

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3.2.2 Stakeholder category and sectoral analysis

In this subsection, we review the distribution of stakeholder categories and sectors across countries.

3.2.2.1 Stakeholder category distribution

Stakeholders are classified according to categories defined in the Stakeholder Engagement Plan (D3.1), which are academia, government, NGO and private sector. We notice that private sector actors represent the largest share of the Stakeholder Council, with 1,328 entries. Government stakeholders are the second largest group, followed by academia and civil society (NGOs). A stakeholder gap exists in NGOs since they represent 12% of the number of private stakeholders and attention should be put on increasing coverage in this group.

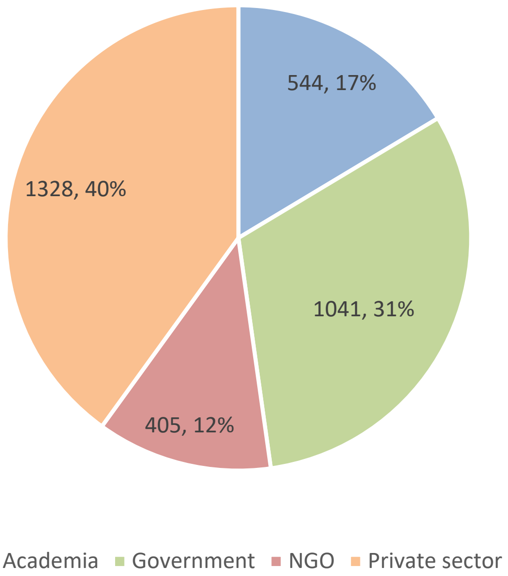

Figure 3: Distribution of stakeholders by category

Looking at the distribution of stakeholder categories across countries in Europe, we notice that, in countries with a large number of stakeholders, coverage is reflective of the overall distribution of the database. We observe however a few significant outliers amongst them: the UK and Spain display a very large share of private sector stakeholders, the Netherlands of NGOs and Belgium of government stakeholders. The latter is linked to the presence of the European institutions in the country.

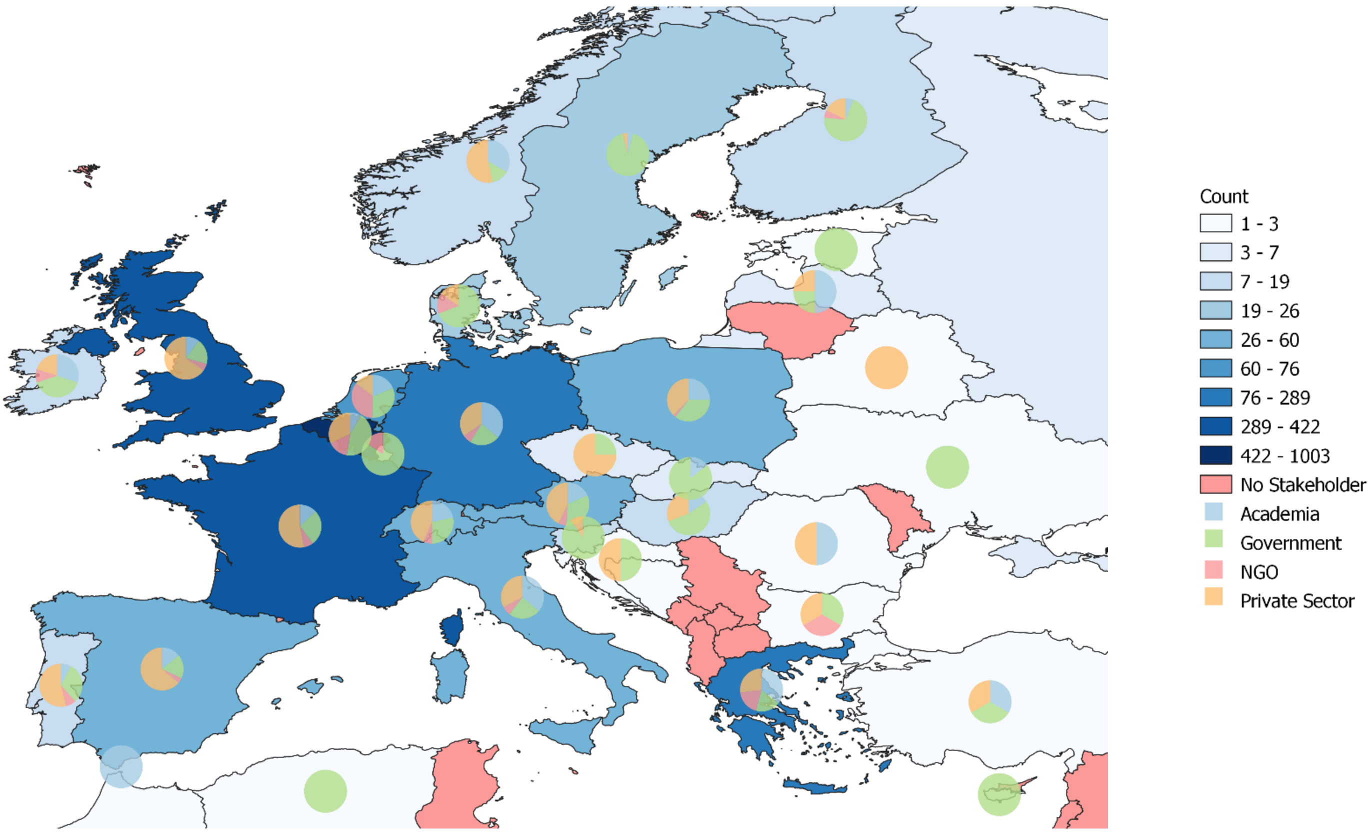

Figure 4: Distribution of stakeholders by category in Europe

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3.2.2.2 Private sector stakeholders

Amongst the private sector stakeholders of the database the two most represented sectors are financial services and energy companies, as together they represent over half of the sample.

From Figure 6, looking at the geographical distribution of the private sector stakeholders, we observe several trends. We notice that Western European countries display the highest concentrations of private sector stakeholders included in the database; however, Estonia and Lithuania do not have a single entry. Also, most countries with a large number of stakeholders display a great variety of sectors among their private sector actors. However, some countries display large concentrations. For instance, banking and insurance companies are heavily concentrated in the UK, in line with London being a major financial centre. Portugal and Norway have a large share of energy private sector stakeholders. Greece has the highest concentration of consulting and law-related private sector stakeholders.

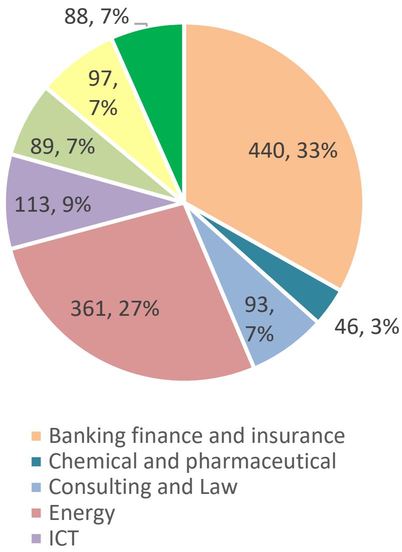

Figure 5: Distribution of private sector stakeholders by sector

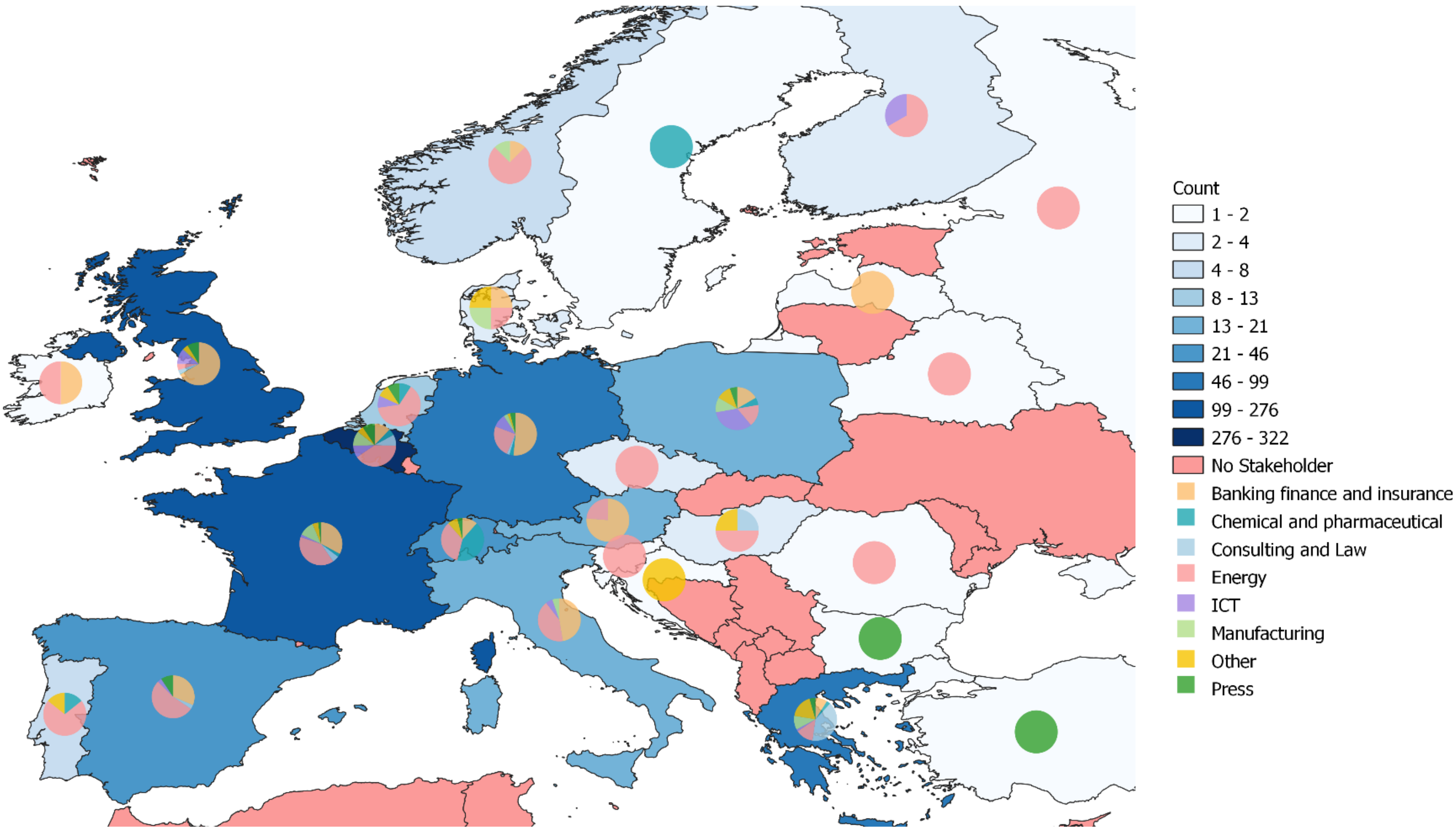

Figure 6: Distribution of private sector stakeholders by sector in Europe

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3.2.2.3 Government stakeholders

Government stakeholders are split between national and supranational governments or organisations. We observe that the majority of government stakeholders are from national government structures, but the database also includes a large number of stakeholders operating in supranational government bodies or international organisations. Other refers to government bodies that were not classified by the algorithm.

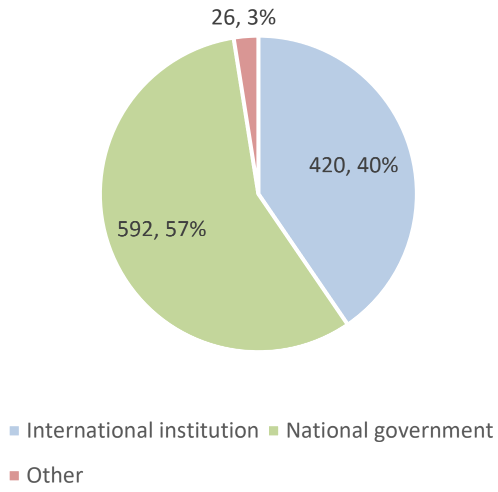

Figure 7: Distribution of government stakeholders by sector

The geographic distribution of government stakeholders is uneven across geographies, but there appear to be no significant gaps in the country coverage in Europe. Romania and Lithuania are the only two EU countries, for which the database does not include a government stakeholder; for Estonia, however, there is only an international government stakeholder holder included. From Figure 8, we notice that, in most countries with a large number of entries, national government stakeholders represent the majority of the stakeholders. This is nevertheless not the case in Belgium and Luxemburg as they host the European institutions.

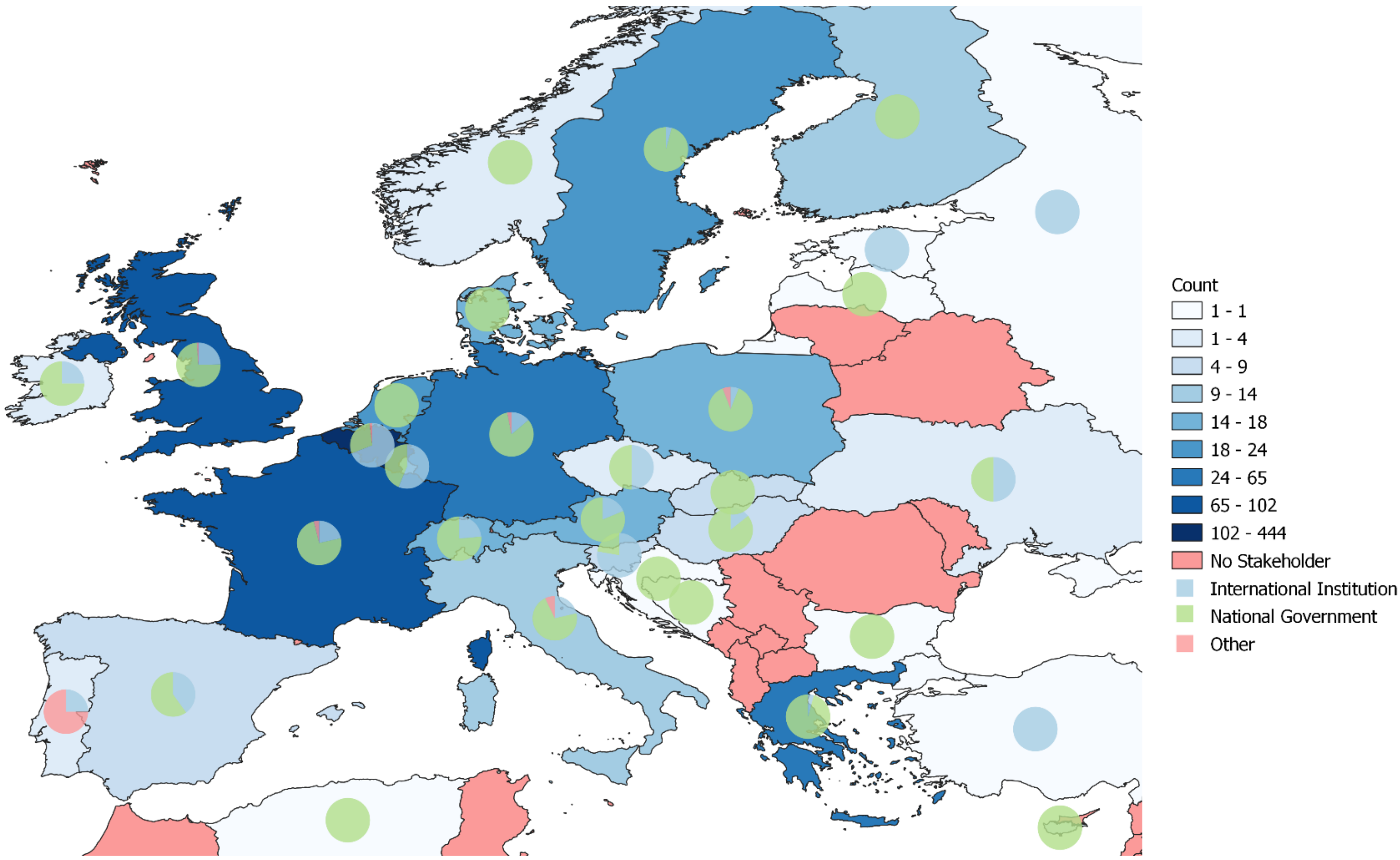

Figure 8: Distribution of government stakeholders by sector in Europe

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3.2.2.4 Academic stakeholders

The organisations of academic stakeholders are categorised as universities, research institutes or basic education structures. Research institutes include think tanks, independent research centres and institutes. Research centres within universities are classified as universities. Academic stakeholders to PARIS REINFORCE mostly stem from universities; nevertheless, many stakeholders are from research institutes as well.

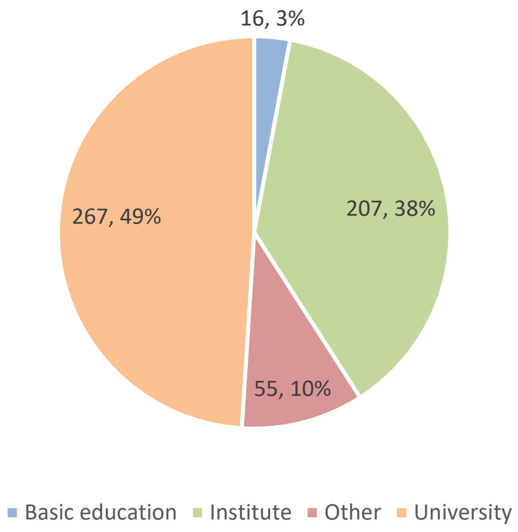

Figure 9: Distribution of academic stakeholders by sector

The geographic distribution of the academic stakeholders in the database displays some gaps. As such, we notice that, for a number of countries, the database contains no entry. Countries in the EU with no academic stakeholder are Austria, Bulgaria, Croatia, Cyprus, Denmark, Estonia, Lithuania, and Luxembourg. Considering the sectoral distribution of the academic stakeholders within countries, we observe that the distributions are rather stable. A few countries display concentrations of specific types of academic stakeholders, including the Netherlands were many stakeholders are affiliated to research institutes or in Poland where most academic stakeholders are associated to a university.

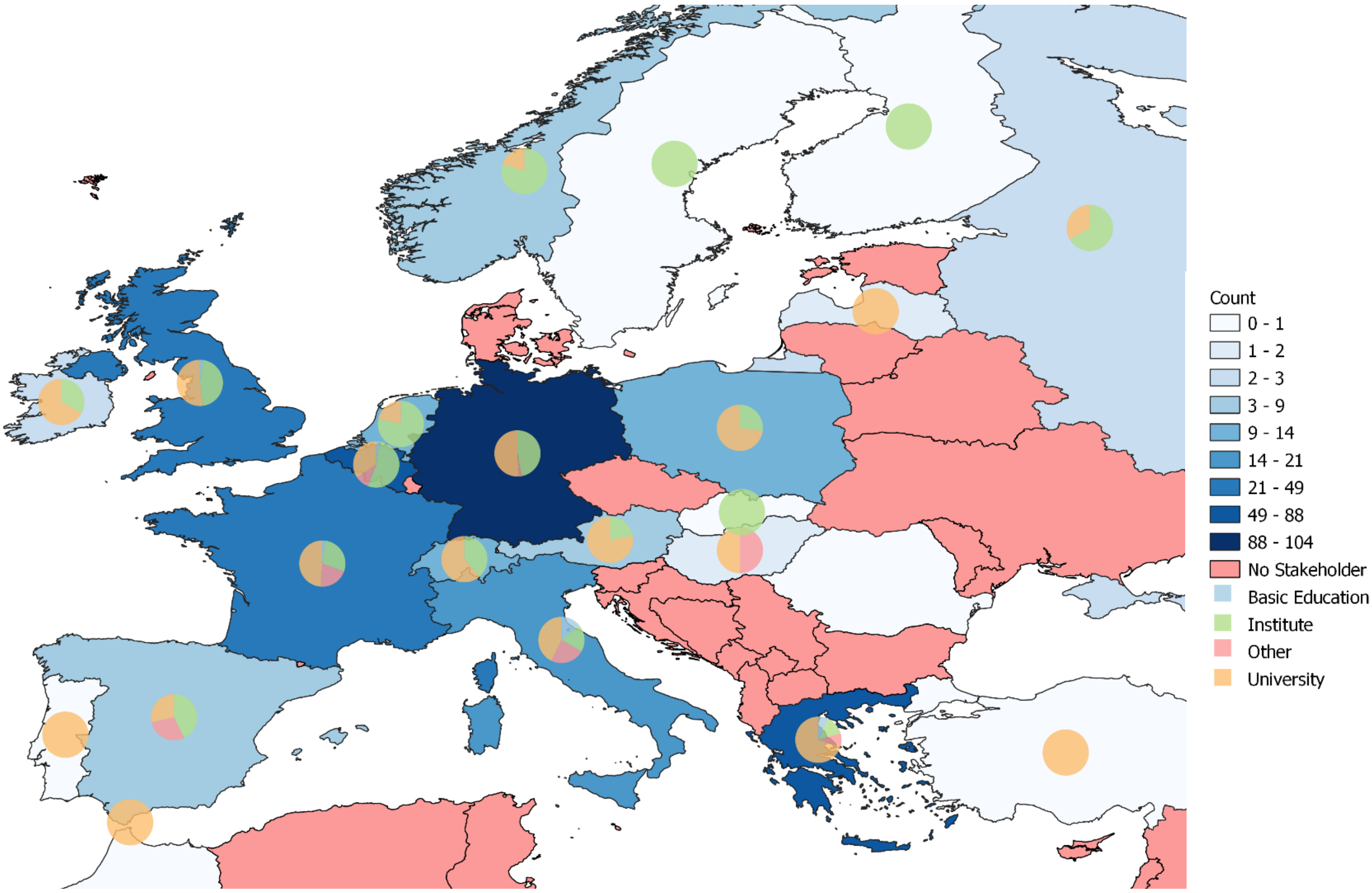

Figure 10: Distribution of academic stakeholders by sector in Europe

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3.2.2.5 NGO stakeholders

Non-government organisations are classified into two subgroups in the Stakeholder Council database: foundations and industry associations. Industry associations include all NGOs that regroup different private sector actors and promote their interests. Foundations is a catch-all term for all NGOs that do not match this definition; in general NGOs included in this category are purpose-driven civil society organisations. We notice that foundations represent a larger share of the NGOs in the Stakeholder Council, in part due to the catch-all nature of this grouping.

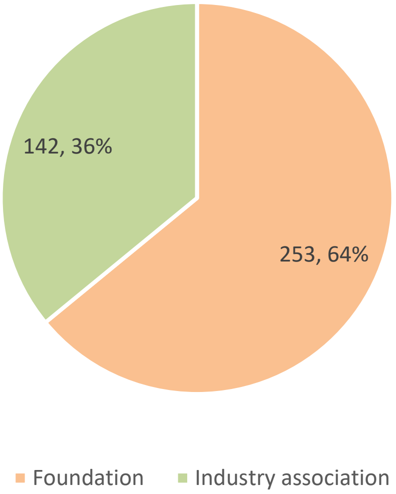

Figure 11: Distribution of NGO stakeholders by sector

Considering the geographical distribution of NGOs in the database, one can observe from Figure 12 that the distribution is very much skewed to the West of Europe. Indeed, the mapping displays a large stakeholder gap in Eastern Europe where, except for one NGO being located in Poland, there are no stakeholders of this type included in the database. Greece, however, displays a large number of NGO stakeholders. For the countries that have NGO stakeholders, we notice that the distribution between foundations and industry associations tends to match the overall distribution of the database. Exceptions to this are Belgium and Denmark, where industry associations appear to be relatively overrepresented.

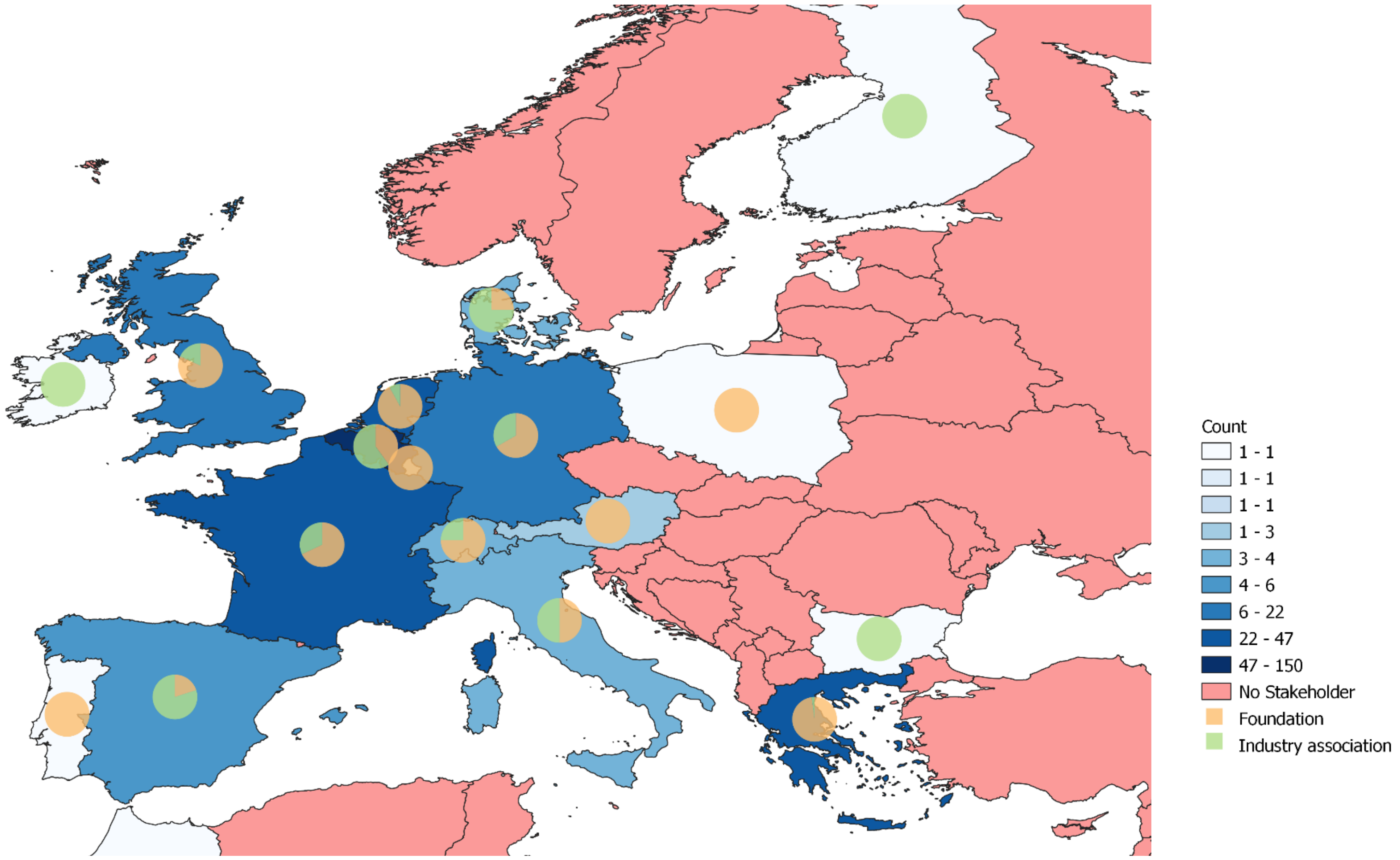

Figure 12: Distribution of NGO stakeholders by sector in Europe

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3.3 Conclusion of the Stakeholder Council database enhancement

In this section, we have augmented the initial Stakeholder Council database and identified gaps in the resulting database. Starting from a database of 3,701 entries, but with limited response rates on certain key variables, the database was enhanced with the objective to make the database useful for stakeholder engagement as outlined in D3.1 and to uncover stakeholder gaps. Supplementary information was added to the database using data processing techniques such as automated Google and Wikipedia searches and NLP. The resulting database reaches coverage rates of around 90% on variables, such as the country where the stakeholder is located, the category of the stakeholder and the sector in which they operate.

Following this, we conducted an analysis to understand where coverage of the database was insufficient to meet the needs of PARIS REFINFORCE. Indeed, to enable co-creation between stakeholders and modellers, a broad coverage in geographies, types and interests is needed. To assess whether the coverage of the database is sufficient, we map out the stakeholders by type and sector and look for potential gaps. We find that the coverage of the Stakeholder Council is widespread geographically, with, however, a large concentration in Western Europe. To improve the worldwide coverage of the Stakeholder Council database, effort should be put into expanding coverage in Central America, the Caribbean, Central Africa, Central Asia, the Middle East and South-East Asia, especially given the project's scope to expand its modelling analysis in countries of said regions.

Considering Europe only, we also looked at the distribution of stakeholders across categories and sectors. The conclusions we draw from this analysis that, although the Stakeholder Council includes many actors from all branches of society, the distribution is somewhat uneven. For the Stakeholder Council to be more balanced emphasis should be put on including more NGOs into the database. The geographic distribution of stakeholders within Europe could also be improved; including more stakeholders from Eastern Europe should be favoured, as well as from the Baltic countries.

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4 Key actor analysis

4.1 Twitter analysis

4.1.1 Introduction

The aim of this exercise is to map out connections between stakeholders of the climate and energy field on Twitter and develop insights to guide stakeholder engagement. The focus is on the online sphere of interaction between policymakers, academic experts, private individuals, and the press. We choose to analyse Twitter, a widely used microblogging website, as it has become a legitimate vehicle for political communication and debate around policymaking (Shapiro & Hemphill, 2017). This is especially true in the case of the discussion around climate change and energy policy, which has become an important topic on the social network and is discussed by a wide array of actors including NGOs, experts, grassroots activists, celebrities and politicians (Fownes, Chao, & Margolin, 2018). This variety is particularly useful to us, since as noted by (Grandjean, 2016), analysing Twitter allows us to cover a broader range of stakeholders beyond the institutional profiles that usually participate in conferences.

Past research regarding climate change on Twitter has mostly focused on assessing public opinion towards the latter (Cody, Reagan, Mitchell, Dodds, & Danforth, 2015). This has been done using various methodologies, for instance by using text analysis to evaluate the proportion of sceptical tweets about climate change in the overall discussion (Jang and Hart, 2015), or the emotional content associated to climate-related tweets, assessing whether this content tended to be negative or positive (Cody et al., 2015). Another stream of research in the field of Twitter and the climate discussion is focused on the geographic distribution of the climate conversation on Twitter, for instance, Kirilenko, Molodtsova and Stepchenkova (2015) found that the US, the UK, Canada, Australia and Norway had the highest relative volume of tweets about climate change. Meanwhile, Jang and Hart (2015) found that in the US, in Republican leaning states climate-related tweets were more likely to use the hoax frame than those from Democrat leaning states. Overall, this section differs from these approaches since we care less about the written content of the tweets and more about the connections between users these tweets create.

In this section, we shed light on aspects of stakeholder interaction such as whether there is an online conversation between policymakers and scientists and which actors are important in fostering such a discussion. Such an analysis also allows for the identification of clusters within the network, providing useful insights into the communities that exist and how they interact. From similar forms of analysis, small world properties have been found in academic Twitter interaction maps, meaning that all actors were highly interconnected amongst each other (Grandjean, 2016). One hypothesis we check is whether there exists a high degree of interaction within the climate and energy science and the climate policy communities but only limited interaction between the two communities. If the former is true, by identifying the connecting stakeholders the following analysis can be used to enhance the policy dialogue between policy institutions and scientists. Another aim of this section is to analyse the structure of stakeholder networks. This concerns looking at inequalities between actors in terms of outreach its community structure. In other words, the analysis investigates what type of online community the climate policy debate exhibits.

We will perform the analysis on two different Twitter networks, based on the same set of accounts which were classified into four categories: policymakers, academic experts, press, and private individuals (citizens). The first network is one in which links are defined as follower connections, the second network defines interactions through tweets including user mentions, replies and retweets. While the first network focuses more on passive interactions between Twitter accounts and amounts to sharing information, the second provides information about active interactions between Twitter users amounting to creating information; this makes their analysis complementary.

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4.1.2 Data

The first network, hereafter named the "followers network", is created from data extracted using the Twitter API, which is freely available, while the second network, named the "tweets network", is created using a premium Twitter API. Both networks rely on a similar group of Twitter accounts, which is obtained using the following method. Starting from 50 handpicked accounts representative of the climate policy and modelling fields, the followers of these accounts are extracted and a subgroup of these accounts is selected, by filtering the accounts and keeping those following at least 10 of the handpicked accounts. This selection yields a list of 1,386 accounts which constitutes, in our view, a representative audience from the climate and energy debate on Twitter. Expert selection of 50 relevant accounts to build the network is a first necessary methodological step. The process of expanding the network implies that all further relevant accounts should be identified.

The next step is to use this representative audience to obtain the accounts of our network. We proceed in recovering all their Twitter friends (people who they follow), and select the 1,000 most central personal accounts, meaning those with the largest number of follows from our representative audience and owned by a physical person. This enables us to create a larger network than the original 50 handpicked accounts while still being representative of the climate and energy Twitter sphere; the method is depicted in Figure 13. We test the robustness of our sample by identifying words related to climate and energy in the descriptions of the accounts we gathered and find that 68% of the accounts in our sample include such words in their description. We consider this figure to be a lower bound, since some people working in (or associated with) the field of climate and energy policy may not include related words in their description and because our list of matching words is non-exhaustive.

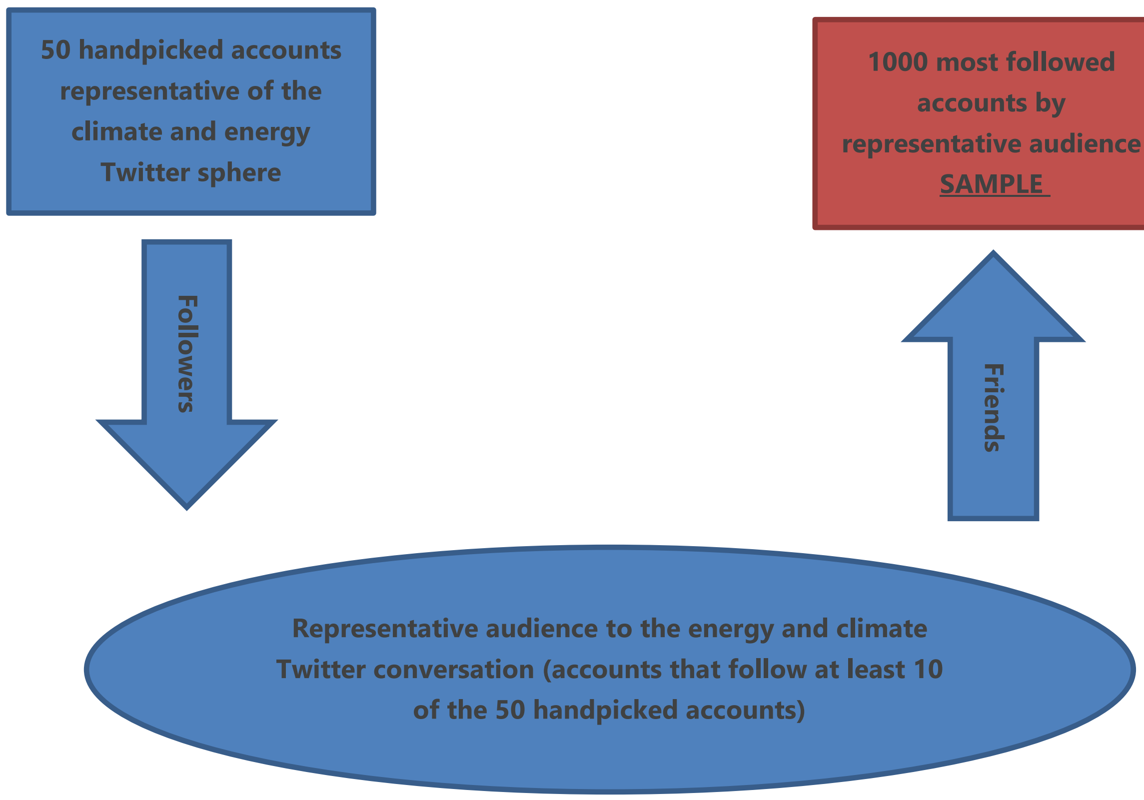

Figure 13: Sampling method of the Twitter accounts

We classify the 1,000 accounts into four categories: policymakers, academic experts, press and private individuals. We define policymakers as the accounts of which the owner is associated to a form of government, either national or supranational, academic experts as scientists working in universities or research institutes, press as individuals

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working for newspapers and magazines either online or print and, finally, private regroups all remaining actors including activists and private sector workers. We achieve this classification in two steps: first, by running a text analysis software on the description of each accounts to create an initial classification; second, by checking the output of the algorithm by hand and filling in the remaining blanks. Table 4 displays a summary of the distribution of categories over the four groups; we notice that the two largest groups are academic experts and private sector actors while policymakers and press actors are less frequent.

Table 4: Summary of category classification of Twitter accounts

Category	Count
Academic Expert	310
Policymaker	201
Press	177
Private	311

From this list of 1,000 accounts we create two networks, one based on the follower and friend connections amongst the accounts, and another reliant on the tweet interactions between the selected accounts. To create the first network, the procedure is straightforward: we simply extract all followers of each of the 1,000 representative accounts and keep only their links with the other members of the list. The second network is reliant on the tweets posted by the 1,000 representative accounts: for each one of them we download the last 500 posts and extract the accounts mentioned in the tweets and, in the case of a retweet, from which account the tweet originated. We then keep only the interactions with the other representative accounts and build a network from this data, where each link represents an interaction, either a mention or a retweet. The tweets are collected over a period ranging from 01-01-2010 to 20-07-2020, but this timeframe might be shorter depending on how far the last 500 tweets of an account reach and whether the account existed in 2010.

4.1.3 Analysis of the networks

The remainder of Section 4.1 is of a technical nature. Boxes at the end of sub-section lay out the key messages that our analysis has revealed.

4.1.3.1 Description of the networks and overall statistics

We start with the analysis of the followers network, in which links are defined as follows. Mathematically the network is defined as a set of nodes called N where $N = \{1 \ldots 1\,000\}$, a set of edges, $E = \{1 \ldots 167\,193\}$, and an adjacency matrix A, defining the connections between N and E. We can therefore define the directed network $G = (N, E, A)$. The average degree of the network is 167 and the density is 17%, while the average path length, meaning the average distance in terms of edges between two nodes, is 1.9. These metrics indicate that the network is rather well connected (17% of all possible connections exist) and that there are on average slightly less than 2 nodes between each possible set of nodes. The longest existing path length is 5 nodes, this is rather high for a network of relatively small size (1,000 nodes).

The tweets network in which links are defined through tweets including other user mentions, replies and retweets may be defined as a set of nodes $N = \{1 \ldots 945\}$, a set of edges $E = \{1 \ldots 32\,207\}$, a set of weights $W =$

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$\{1 \ldots 32\,207\}$ assigned to each edge and an adjacency matrix A. The weights are defined as the sum of the interactions between accounts; thus, if two accounts interacted twice, in the same direction, for instance if one account retweeted the content of a same account twice, the weight will be equal to two on the directed link from the first account to the second. The network of tweets can therefore be defined as $G = (N, E, A, W)$. For the tweets network we observe an average degree of 34, a density of 3.6% and an average path length of 2.8, the longest path length in this case being 9. These metrics indicate that the tweets network is more sparsely connected than the followers network. Thus, in line with expectations, tweet interactions are less frequent than follows between users, reflecting that while users have access to each other's information extensively, they communicate much less frequently.

The followers network is more tightly knit than the tweets network, reflecting that while many actors follow one another, actual interactions are much scarcer. Indeed, on average people in the network are following or being followed by 164 others while only interacting with 34 people.

4.1.3.2 Degree distribution

The degree distribution refers to the relationship between the degree of the nodes (number of connections) and the probability of a node to have a given degree. In the literature, many networks have been observed to feature scale-free properties, meaning that their degree distribution follows a power law, $P(k) \sim k^{-\gamma}$, where $p(k)$ is the fraction of nodes in the network having k connections to other nodes and γ is a parameter taking values $2 < \gamma < 3$ in general (Newman, 2018).Such networks have a relatively large number of highly connected nodes, and therefore have small world properties associated with rather low levels of density. From a practical perspective, these networks are therefore highly reliant on a set of highly connected nodes for their overall connectivity and the transmission of information across nodes. Scale-free networks have been found in a variety of fields, in biology when considering the composition of cell (Albert, 2005) or in economics when considering the US interbank market (Soramäki, Bech, Arnold, Glass, & Beyeler, 2007). However, more recent evidence points towards log-normal degree distributions to be the most frequent organisation of empirically observed networks (Broido & Clauset, 2019).

Evaluating the degree distributions of our networks we obtain the results displayed in Figures 14 and 15, where for both networks we display the degree distribution, the indegree distribution (indegree meaning the number of incoming edges) and the outdegree distribution (conversely, outdegree meaning the number of outgoing edges).

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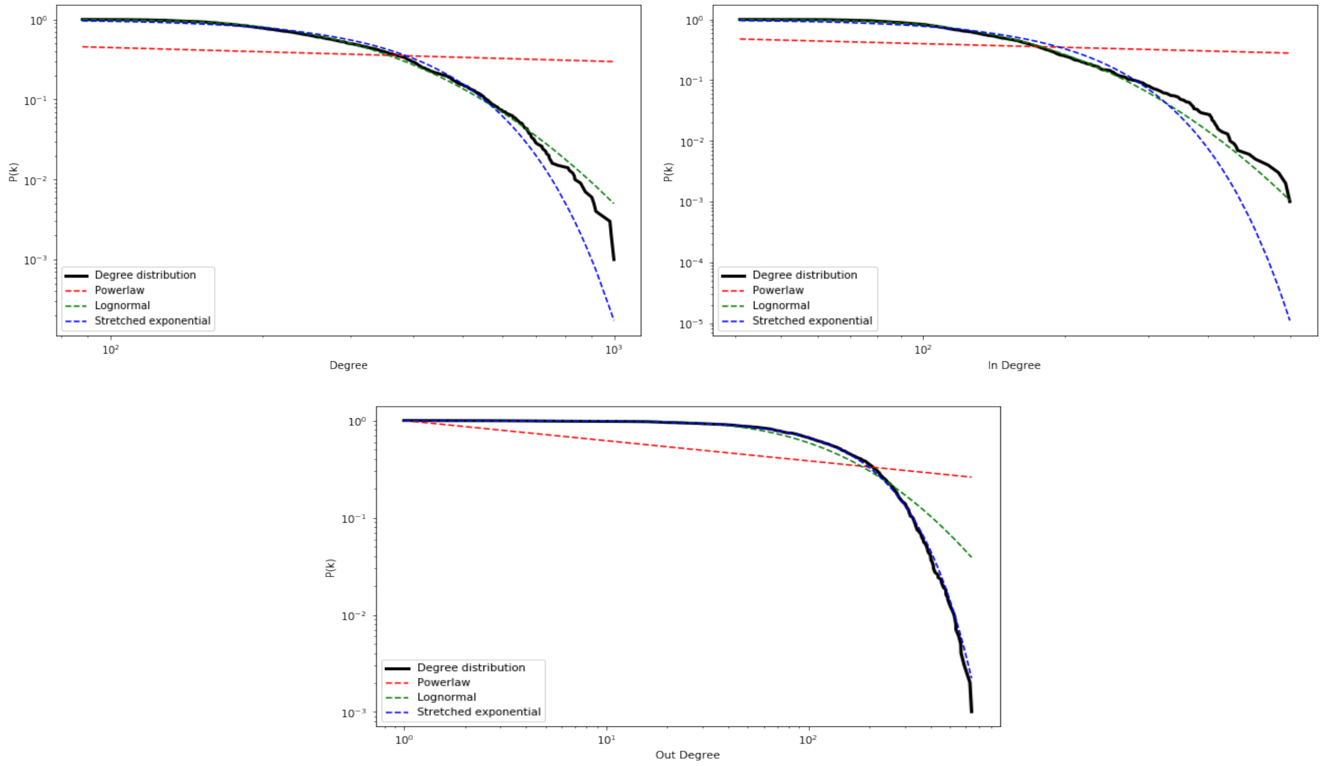

Figure 14: Degree distributions of the followers network

Note: The axes of the figures are in log-scale. The x-axis represents the degree, being the number of connections of a node; the indegree, being the number of incoming connections; or the outdegree, being the number of outgoing connections. The y-axis represents p(k) being the cumulative probability for a node to have a degree greater than k. The three dotted lines represent fitted statistical distributions as indicated in the legend. The black line is the degree distribution of the network in question.

From Figure 14 we notice that the followers network's degree distribution tends to follow an exponential distribution rather than a power law. To be precise, the degree distribution and the indegree distribution both match a log-normal distribution, while the outdegree of the nodes follows a stretched exponential distribution. Both of these distributions have less heavy tails than a power law distribution, especially the stretched exponential which the outdegree distribution follows, indicating a lower prevalence of extreme values compared to a scale-free network. The difference between the indegree and outdegree distributions also indicates that there is more homogeneity in terms of the outdegree of the nodes compared to the indegree of nodes. One implication of this observation is that, since the indegree of an account can only be increased by the decision of other accounts to follow that specific account, it is more reflective of authority within the network than having a high outdegree, which is defined by one's own decision to follow many other accounts. It follows that there is more inequality in terms of indegree.

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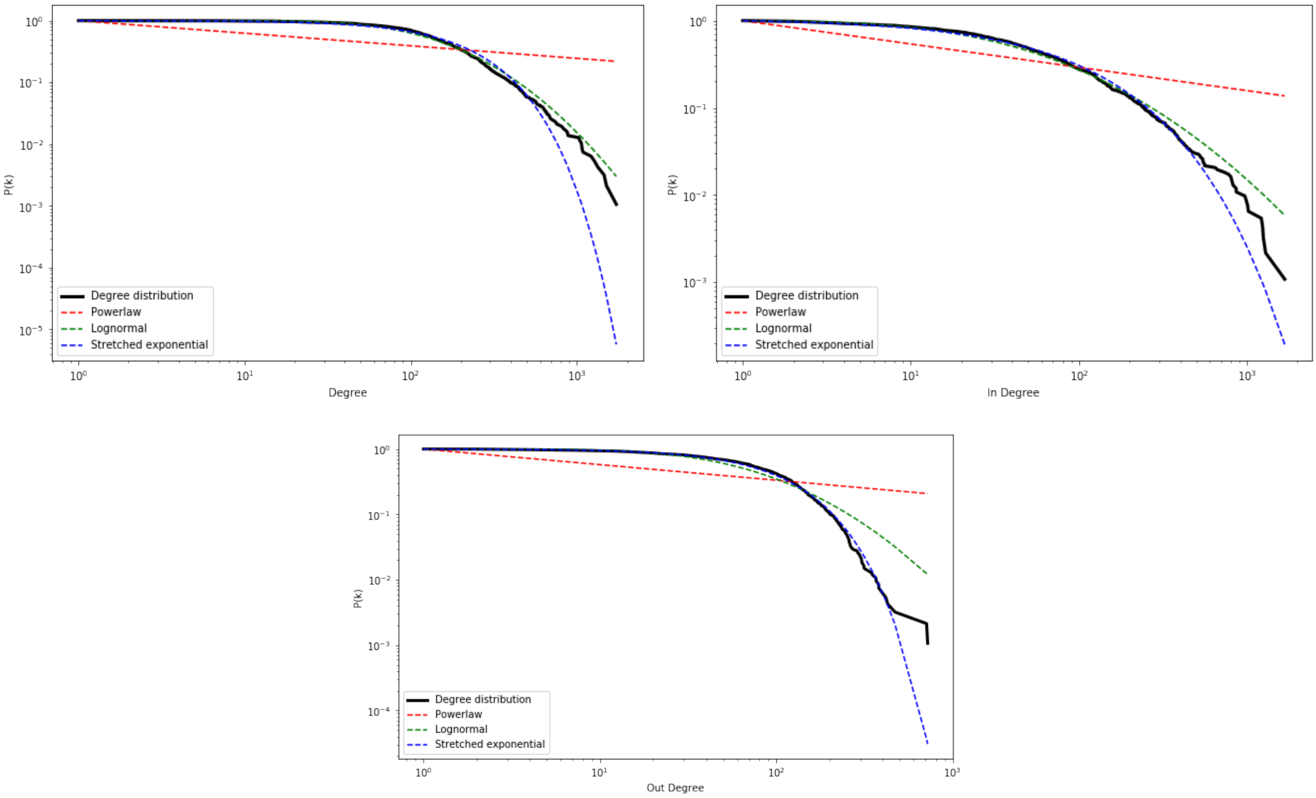

Figure 15: Degree distributions of the tweets network

Note: The axes of the figures are in log-scale. The x-axis represents the degree, being the number of connections of a node; the indegree, being the number of incoming connections; or the outdegree, being the number of outgoing connections. The y-axis represents p(k) being the cumulative probability for a node to have a degree greater than k. The three dotted lines represent fitted statistical distributions as indicated in the legend. The black line is the degree distribution of the network in question.

Figure 15 displays the degree distributions of the tweets network. Similarly, we notice that the distributions of the degree and the indegree point towards a log-normal distribution, while the outdegree distribution appears to follow a stretched exponential distribution. This pattern matches that of the followers network, implying that in terms of the distribution of the number of interactions between Twitter users, the difference between active and passive interaction is small.

The number of connections each node has is unequally distributed, meaning that some people have a lot of influence and are followed or talked to by many people, while others much less. This implies that some actors are more important than others, and these important people are few compared to what has been observed in other empirical networks (Newman, 2018)**.**

4.1.3.3 Centrality analysis

Considering the centralities of the nodes, meaning their relative importance in our networks according to different measurements, we make several assessments. Looking first at the 50 accounts with the highest betweenness

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centrality[2], meaning those with the highest number of shortest paths running through them, we notice important differences between our two networks (Annex 5.2 contains the detailed list of the most central accounts based on betweenness in both networks). First the academic experts are much more represented in the top 50 of the tweets network compared to the followers network, since betweenness centrality is high for accounts that link together many other individual and clusters of accounts; academic experts play an important role, through active interaction, in connecting members of the climate and energy policy sphere. Indeed, they represent nearly half of the 50 most influential accounts in linking others through tweets, while representing only about one third of the sample. This contrasts with the policymakers, who are underrepresented in both networks. Meanwhile, accounts belonging to the category "press" represent exactly their share in the overall population in both networks.

Table 5: Frequency by account category of the 50 accounts with highest betweenness centrality

%	Share population	Share top50 Followers	Share top50 Tweets
Academic Expert	31	36	46
Policymaker	20	10	18
Press	18	18	18
Private	31	36	16

Considering another centrality measurement, the page rank centrality (Brin, Page, Motwani, & Winograd, 1999), a measure where nodes derive their own centrality from the centrality of their neighbours in a recursive process. Nodes with high page rank centrality in our networks will be those that interact with other important accounts and should represent in a sense the "elite" of the network. We observe in Table 6 the distribution between categories of the 50 accounts with the highest page rank centrality. Here we notice in both networks that policymakers are heavily overrepresented in the 50 most central nodes according to Page rank. This stems from their linkages with other influential accounts and points towards a policy elite existing in the network.

Table 6: Frequency by account category of the 50 accounts with highest Page rank centrality

%	Share population	Share top50 Followers	Share top50 Tweets
Academic Expert	31	22	24
Policymaker	20	44	40
Press	18	10	16
Private	31	24	20

To check if the trends we noticed in Tables 5 and 6 can be extrapolated to the whole sample, we calculate the

[2] See Grandjean (2016) for more discussion.

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average centrality of the nodes by category and standardise the output. The results of this procedure are displayed in Table 7 below. We notice that in terms of betweenness centrality the 'press' category has the highest average betweenness centrality in the followers network, while the 'expert' category has the highest average for the tweets network. This result contains two important pieces of information: first, it suggests that the press plays its expected role as an information bridge between different groups; second, while the press is well connected in terms of "following" links, academic experts lead in terms of active online interactions and appear to foster more of a discussion between the actors of the climate and energy Twitter network. Regarding the page rank centrality results, we have the confirmation that policymakers display a high level of importance according to this metric, also for both networks as a whole. This confirms an elite-like structure where policymakers are connected with other high-profile accounts. We see below if these accounts are also those of policymakers or if policymakers tend to interact with all types of actors in the network, which still tend to be of higher relative importance.

Table 7: Average centrality by category, standardized values

	Followers		Tweets	
Category	**Betweenness**	**Page Rank**	**Betweenness**	**Page Rank**
Academic Expert	0.07	-0.91	1.49	-0.34
Policymaker	-1.44	1.51	-0.83	1.69
Press	1.38	0.30	0.33	-0.41
Private	-0.02	-0.90	-0.99	-0.93

As such, we evaluate the homophily (Himelboim, et al., 2014) of the different categories in the network; in other words, we check with which other categories individuals from one specific category tend to form links with. In Table 8 we display the results for both networks, where for each category we present the share of their connections with nodes for each category including 'their own kind'. From Table 8 we notice crucially that both policymakers and academic experts tend to communicate to a disproportionate degree with their own kind. Indeed, in both networks we analyse, and especially in the tweets network, we observe that policymakers and academic experts conduct respectively 48% and 43% of their active interactions with peers of their category. The difference between the followers network and the tweets network is also noteworthy, it indicates that meaningful interactions are more internal to one's group for policymakers and academic experts compared with passive interactions. The rather inward preferential attachment pattern of the previously mentioned two groups contrasts with the two other groups, whose interactions with accounts from a different category are roughly proportional to the absolute size of each group. Although we should remind ourselves that these results stem from a single, but important, online platform, this finding is key in that it makes a strong case in favour of building stronger ties between policymakers and academic experts.

Table 8: Share of connections between different categories

Followers network				
From\To	**Press**	**Academic Expert**	**Policymaker**	**Private**
Press	0.26	0.28	0.18	0.28
Academic Expert	0.18	0.39	0.14	0.29
Policymaker	0.17	0.23	0.34	0.26

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Private	0.19	0.30	0.18	0.33
Tweets network				
From\To	**Press**	**Academic Expert**	**Policymaker**	**Private**
Press	0.30	0.29	0.18	0.23
Academic Expert	0.17	0.43	0.16	0.24
Policymaker	0.12	0.19	0.48	0.21
Private	0.18	0.30	0.22	0.30

We consider two measures of importance within a network, one showing the importance of a person as bridge between communities, the other showing the importance of a person due to its connections with other important people. We notice that, for our networks, academic experts play the role of bridging the different communities and policymakers are the most "well connected" in terms of being linked to other important members of the network.

We notice that both of these trends (i.e. bridge and importance) are stronger when it comes to interacting through tweets with other members compared with simply following other members. We also notice that academic experts and policymakers tend to follow and interact mostly with people of their own category. This is even more true for tweet interactions, telling us that these two groups follow each other's

4.1.3.4 Community detection

As a final analytical step, we aim to identify communities within our network. To this end we divide the networks into modularity classes where the modularity is, up to a multiplicative constant, the number of edges falling within groups minus the expected number in an equivalent network with edges placed at random. To best appreciate the modularity structure of our networks we plot them and assign a colour code to the different modularity classes. Overall, we notice no clear pattern of certain categories clustering together, especially in the followers network. In the tweets network we notice that the distribution is overall quite even except for modularity class 4 which displays a large concentration of academic experts. This is surprising as we have seen in the previous section that there appeared to be a preferential attachment pattern between members of the same category.

Table 9: Distribution of categories by modularity class, percentage of total number of nodes in class

Followers network				
Modularity class	**Academic Expert**	**Policymaker**	**Press**	**Private**
1	38.5	15.6	16.7	29.2
2	23.8	15.0	23.8	37.3
3	18.3	44.2	12.2	25.2

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4	44.0	6.6	17.9	31.6
Tweets network				
Modularity class	**Academic Expert**	**Policymaker**	**Press**	**Private**
1	36.3	9.6	23.8	30.4
2	34.4	17.8	17.8	30.0
3	21.2	15.6	21.6	41.6
4	61.8	6.9	9.2	22.1
5	17.1	44.9	12.0	26.1

Considering other potential drivers of the observed modularity classes, namely the geographical distribution of the classes, we make the following discoveries. By evaluating the location variable of the Twitter accounts in our sample and how modularity classes were assigned to each account in both networks, we derive an approximate modularity distribution by geographic point of gravity. For instance, modularity class 1 in the followers network is heavily dominated by accounts located in Germany, while class 3 seems to capture the Brussels policy network. Only for modularity class 4 in the tweets network we do not find a clear geographic pattern; it is, instead, best defined as grouping of climate and energy experts from all over the world.

Table 10: Geographic distribution of modularity classes

Followers network		
Modularity class	Geographic area	Colour in figure 16
1	Germany	
2	UK	
3	EU	
4	USA	
Tweets network		
Modularity class	Geographic area	Colour in figure 17
1	USA	
2	Germany	
3	UK	

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4	None	
5	EU	

In Figures 16 and 17 we display plots of the two networks rendered using an algorithm implementing a force directed layout, meaning it simulates a physical system in order to spatialise a network. Nodes repulse each other like charged particles, while edges attract their nodes, like springs. These forces create a movement that converges to a balanced state and reflects the modularity classes. Based on the observations made in table 10 we notice several interesting elements in Figures 16 and 17. First we notice that in both the tweets network and the followers network, the EU (in orange) and the US (in green) are polar opposites to each other. Between them we find the two other geographic cluster of the UK (purple) and Germany (Grey) with, seemingly, the UK cluster more attached to the US cluster and the German one to the EU, as one would expect. The location of the "global climate and energy experts" modularity class (Nr 4) in the tweets network is located between the UK and US clusters, reflecting the importance of Anglo-Saxon universities in terms of influence in the academic world.

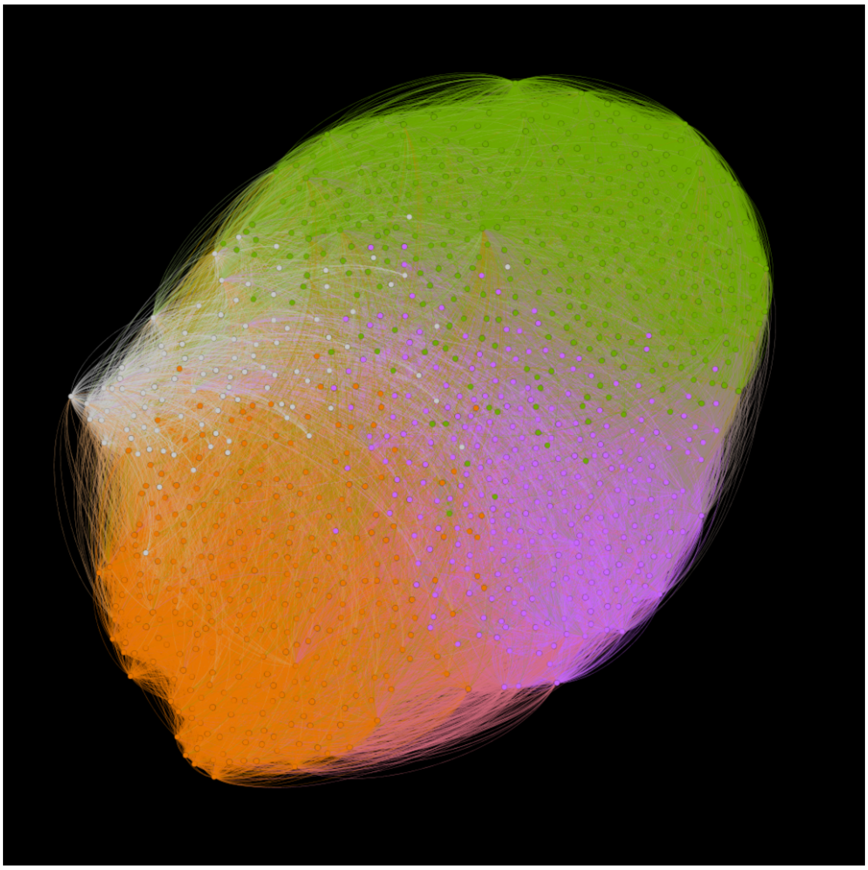

Figure 16: The followers network by modularity class

Note: Each dot represents a twitter account and each link represents a "follow" follow relation. The position of each dot in the representation is defined by an algorithm, which pushes dots together when they are linked and away when they are not. The colour of the dots is defined by modularity, which is an algorithm to detect communities, by comparing the interconnection in the network compared to a situation where the links would be made at random.

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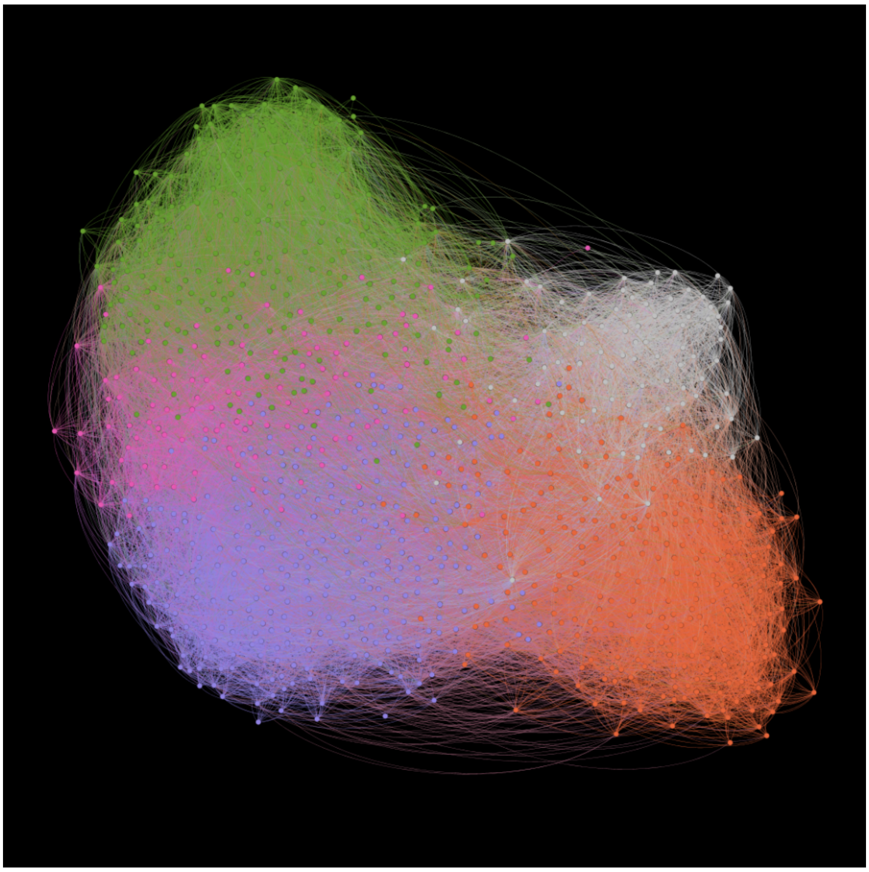

Figure 17: The tweets network by modularity class

Note: Each dot represents a twitter account and each link represents a "tweet" follow relation. The position of each dot in the representation is defined by an algorithm, which pushes dots together when they are linked and away when they are not. The colour of the dots is defined by modularity, which is an algorithm to detect communities, by comparing the interconnection in the network compared to a situation where the links would be made at random.

Using a community detection algorithm, which compares the distribution of the links compared to a situation with links made at random, we discover that our network's communities are not defined by the categories of the persons but by their geographical attachment. As such, we notice a German, an EU (Brussels bubble), a UK and an American cluster. Connecting this finding to our centrality results, it implies that experts do a global job in connecting communities and discussing climate matters; on the other hand, policymakers are very focused on their own geographical areas but yield significant influence at that level.

4.1.4 Conclusion

In this section we build and analyse two networks representative of the climate and energy conversation on Twitter. We have one network where links are formed based on follow relations, another where links are based on mentions and retweets of other accounts. We classify the accounts in our network in four distinct categories; policymaker, academic expert, press and private. As such, we aimed to gain an understanding on the level of interaction between the actors of our network stemming from different categories while also getting a better picture on the structure of the network overall.

We notice that the energy and climate policy Twitter community is quite tightly knit, with 17% of all possible links

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being existent for the followers network. However, these passive interconnections, leading to information being shared between two users do not necessarily imply an active interaction between the two users. As such, the tweets network has a much lower level of density, amounting to 3.6%. Assessing the degree distribution of our networks we do not find evidence supporting the existence of a power law, a distribution found in other empirical networks and distinctive because of its "heavy tail" nature. Instead, we observe exponential distributions for both networks, indicating that degrees are more homogeneously distributed relative to power law distributed ones. It is also interesting that the indegree's distribution has a heavier tail than that of the outdegree in both networks, which can be explained by the fact that individuals can increase their own outdegree by following other accounts, while indegree is more reflective of social recognition and therefore harder to increase.

Our next step was to consider the centrality or "importance", of the nodes in our network and classify them accordingly. To this end we used two centrality measures, betweenness, which evaluates the importance of nodes as bridges between communities, and page rank, which gives importance to nodes connected to other important nodes. Our first important observation was that policymakers had a relatively low level of betweenness centrality indicating that they tend to interact mostly within their own communities. As we uncover, in both networks communities are mostly defined at a geographic level; the isolation of policymakers can therefore be explained by their natural domestic focus. Conversely, policymakers displayed by far the highest levels of page rank centrality. This is reflective of a political circle, which attracts the attention of all members of the network, making these interconnections valuable in terms of page rank. Academic experts in our network are particularly important in terms of betweenness in the tweets network; this may be explained by the important role they play in creating knowledge thereby informing and stimulating the discussion. Their role as bridge between communities in the network also indicates the global nature of their work: they are less domestically focused than other groups in that sense. Finally, considering the attachment of the four groups amongst each other we find informative heterogeneity. We notice that particularly when it comes to active interactions, policymakers and academic experts tend to communicate by a disproportionate amount with their own kind. The fact that this trend is stronger in the tweets network compared to the followers network is not trivial; it indicates that whilst the two groups tend to follow each other's work, they do not necessarily interact online.

The final step in our analysis was the detection of communities within our networks using modularity. Contrary to our initial hypothesis, communities were not necessarily divided by category but rather by geographic attachment. As such, we found in both networks a European, a German, a UK and a US centred group of accounts. In the tweets network we found nonetheless a supranational group of academic experts, although leaning towards the Anglo-Saxon world.

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4.2 Climate and energy conference participant and conferences network analysis

4.2.1 Introduction

In this section, we focus on conferences on the climate and energy field. We investigate the structure of these events and the people who presented. Behind this approach is the idea that the network between speakers is representative of the influencing process. We analyse the network under the prism of policymakers/experts/ lobbyists. The focus of the study is the most central actors, the role played by lobbyists and experts, the heterogeneous communication between different topics, and the links between institutions. We looked at conferences held by the EU, the IEA, and the OECD. Our study could be extended to a larger framework; however, the transformation and collection of data is resource-intensive.

Very few studies to our knowledge analyse the networks of people around a political decision-making process on climate issues, e.g. for South Korea (Jackson, 2011) and Queensland, Australia (McAllister, McCrea, & Lubell, 2014), which looks at the links created through events by focusing on the roles of different types of organisations. Only one study we are aware of focuses on networks of stakeholders in a European decision-making process. It concerns tobacco regulation (Weishaar, Amos, & Collin, 2015). We used this literature to analyse the networks in our study. However, we are analysing a large network, with more than 3,500 people, which is larger compared to the other studies.

To structure our analysis, we base our work on three networks. The more complete was built using all the data available. It is a network analysing the links between all speakers. The second was built using only selecting speakers who attended conferences from different institutions and DGs. The last network is a network of events, allowing an analysis focused on the relationships between them.

4.2.2 Data

We obtained the data from online participants lists to energy and climate policy-related events. The lists are collected from the webpage, cleaned and included in the network. We have collected data about climate change events and meetings inside international organisations (EU, OECD, and IEA). We first made a list of those different events. For each event, we gathered some general information (date of the event, name, weblink). Then, for each event we extracted the list of speakers, and recorded their names and their function. We obtained a total of 273 events and 4,304 speakers. For each of the participants we then manually determined if they were a) a policymaker, b) an expert (scientific expert, economic expert), or c) a lobbyist (from companies or NGOs). We used the following approach to this end. First, the labelling was done abstracting from the conference to which the person had attended and the institution they came from, to avoid any bias. The fact that we indeed found recurrent and coherent patterns showed that our approach was relevant. In the next step, we considered for each person the organisation that this person belonged to and their job. We then defined their category by answering to the question: what drove this person to come to the conference? If they had a direct influence on the policies or had responsibilities in an operational institution, they were labelled a policymaker. If they had technical knowledge and belonged to a “scientific” organisation, they were labelled an expert. If they defended interests of an NGO or a company, even if they were an expert, the person was considered as a lobbyist. This approach is not fault-proof and there is subjectivity involved, but our labelling choices were consistent.

In our analysis we use three different networks, one including all speakers, which contains 4,305 nodes and is depicted in Figure 18. We notice that the structure of our data reflects many clusters, as there are many speakers in each conference, which are therefore all linked, thereby creating a sub-cluster. These subclusters associate into

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supra-clusters due to institution aggregates (e.g. EU events). The interesting individuals are often outside of the clusters. To capture these individuals, we delete the cluster bias, and create a network containing only participants to conferences affiliated with at least 2 institutions/DGs. It contains 158 nodes and is depicted in Figure 19. This network is promising because it is far less clustered and it shows clear tendencies, such as that we find in the left of the graph many lobbyists, in the right experts and in the middle the policymakers. We investigate and explain these characteristics later on. Finally, we create a network of events to understand their structure and interactions: we classify the events by institution and DG for the EU events; this network contains 321 nodes and is depicted in Figure 20. In Table 11, we display the summary statistics of the three networks we built. Table 12 shows distribution of categorires by network.

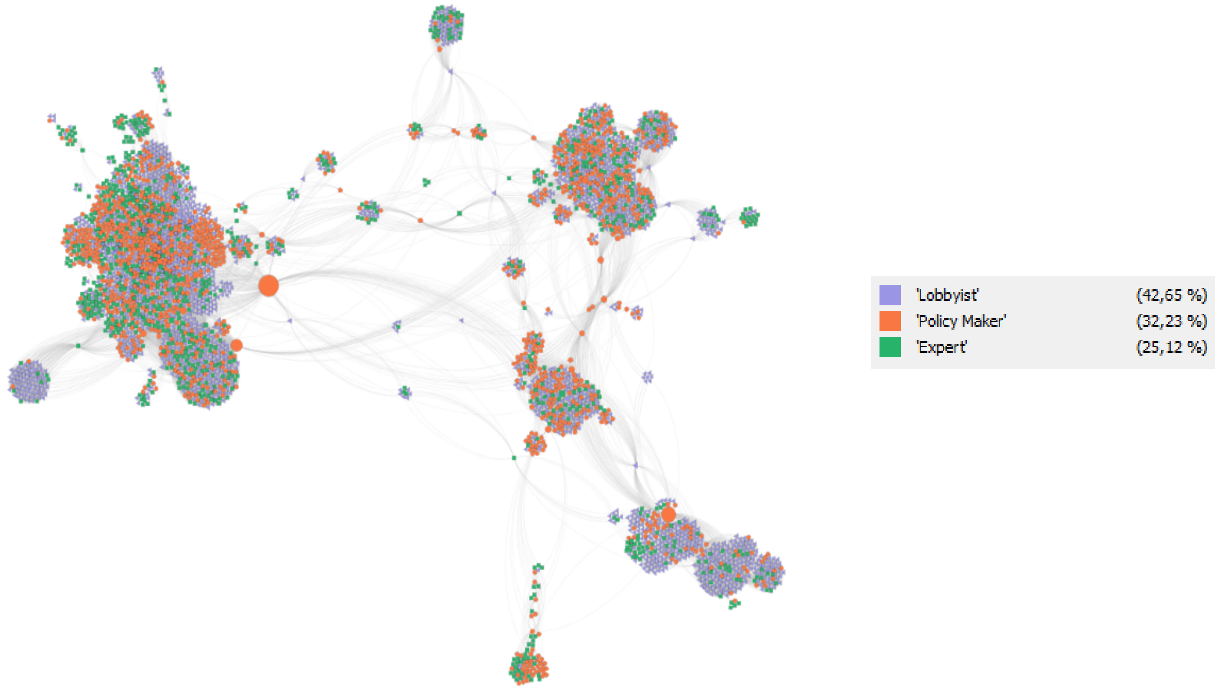

Figure 18: Network with all speakers

Note: Each dot represents an individual, who is either a lobbyist (purple), a policymaker (orange) or an expert (green).

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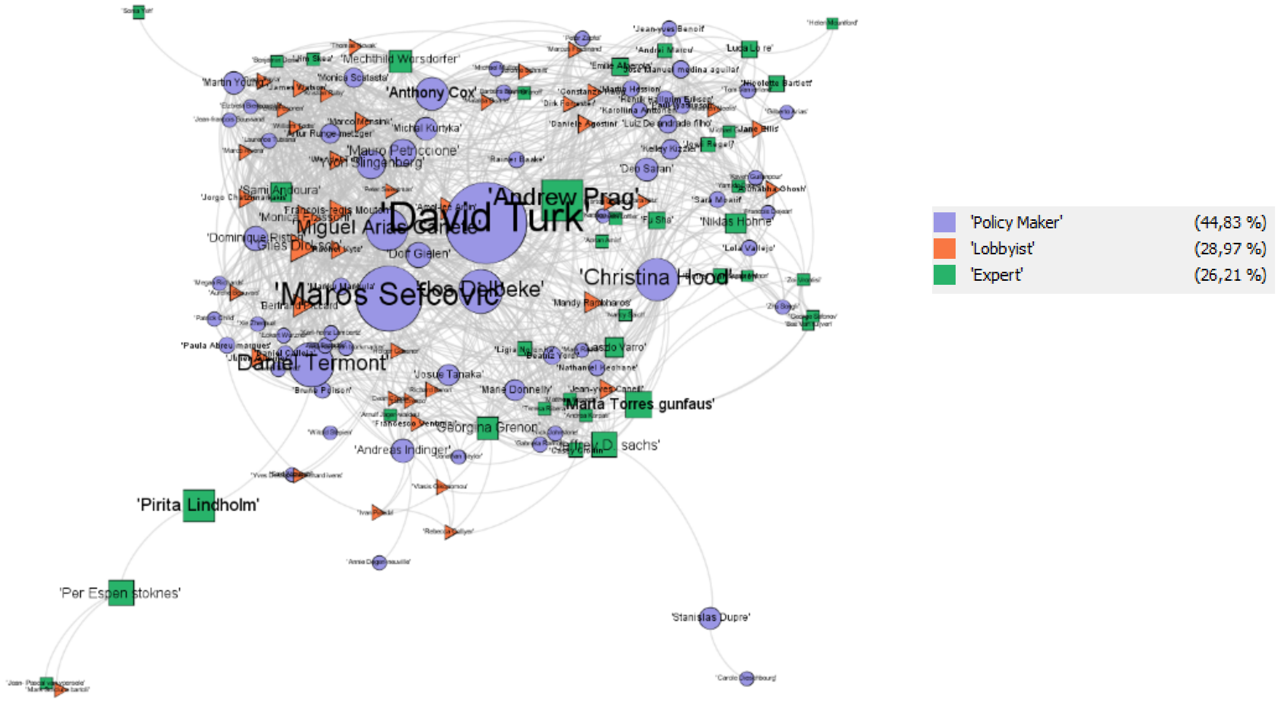

Figure 19: Network with cross-institutional actors

Note: Each dot represents an individual, who is either a lobbyist (purple, circle), a policymaker (orange, triangle) or an expert (green, square).

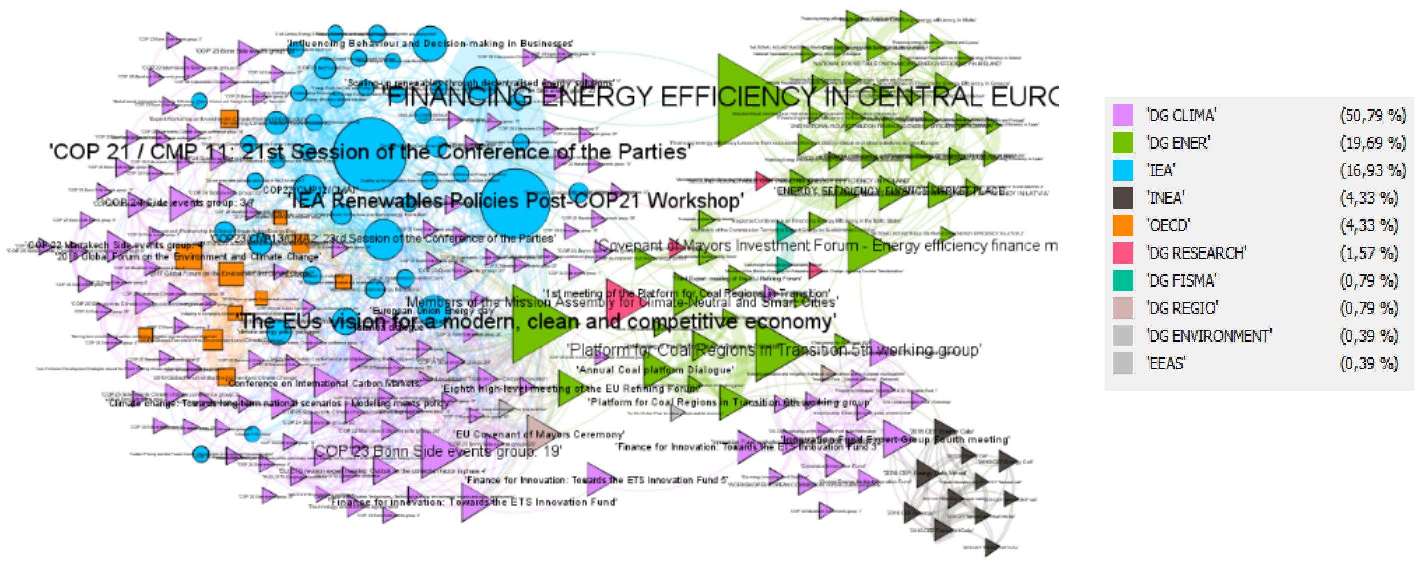

Figure 20: Network of events

Note: Each dot represents an event and the colours represent the institution/DG that hosted it, meanwhile EU events are represented by triangles, IEA meetings by circles, and OECD events by squares.

Table 11: Descriptive statistics

	Network 1	Network 2	Network 3
Description	**Speakers graph network**	**Important speakers network**	**Events graph network**
Number of nodes	4,305	158	321

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Number of nodes in the main component	3,754 (87%)	145 (92%)	254 (79%)
Density	0.01	0.15	0.04

Table 12: Distribution of categories by network

	All speakers	Important speakers
Policymakers	32,2%	44,8%
Experts	25,1%	26,2%
Lobbyists	42,7%	29,0%

4.2.3 Analysis of the actors' networks

The following section is of a technical nature. Similar to Section 4.1 boxes are added at the end of each section so that the reader is able to quickly distil the key findings.

4.2.3.1 Connectivity

For networks 1 and 2, the main component contains 87% and 92% of the nodes respectively. Some simulation showed that it should be statistically 100%. The way to explain it is that the events correlate the links. The fact that the people meet on limited occasions, make the networks very close, and less diversified. Also, the diversity in the number of links makes some speakers isolated. The density of network 1 is 0.015 and the density of network 2 is 0.146. This higher density confirms the relevance of considering the subnetwork, as its members have 10 times more links together than the average.

It is interesting to compare the variation in the degree repartition. In the important speakers network, we only selected highly connected people. As a consequence, the profile is much more parallel, and we see that most nodes are linked to an important proportion of the network (density = 0,15). We can link such profiles to the spreading of an epidemic. The mean number of nodes is R_0, the dispersion is K. To be explicit, in an epidemic (this also applies to the spread of ideas), super contaminators can take a more or less active role. The number K quantifies the importance of big actors in the propagation (Bettencourt, Cintron-Arias, Kaiser, & Castillo-Chavez, 2006). To illustrate this phenomenon, we compare in Table 13 the coefficient of variation defined as ${}^{\sigma}/_{\mu} = \sqrt{{}^{K}/_{\mu}}$. We observe that network 1 is much more unequal than network 2.

Table 13: Coefficient of variation of the networks

	Network 1	Network 2
Description	**Speakers graph network**	**Important speakers network**
Coefficient of variation	1.06	0.68

We also verify the existence of a "small world effect" in our networks, which are well documented in the literature (Hagberg, A., & Swart, 2008), (Sporns & Zwi, 2004), (Ströele, et al., 2018), (Telesford, Joyce, Hayasaka, Burdette, & Laurienti, 2011). Such networks have high transitivity («the friend of my friend is my friend») and short path lengths (distance between nodes in terms of other nodes in between).

We use the transitivity σ and closeness index ω. A small world is characterised by σ>1 and ω close to 0.

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Table 14: Small world effects

	σ	ω
Network 1	8	-10
Network 2	1.8	-0.06

Both networks 1 and 2 have high transitivity values since the people meet in the same conferences and thus meet in groups. Only network 2 has short paths between individuals and can be considered as a small world. These observations suggest that propagation is easier on the network with important speakers than on the network with all speakers.

Considering the degree distributions for both networks we notice that network 1, or the speakers network, has a much more heterogeneous degree distribution compared with the important persons network, with many nodes having a small number of connections. The degree distributions of both networks are depicted in Figure 21 below.

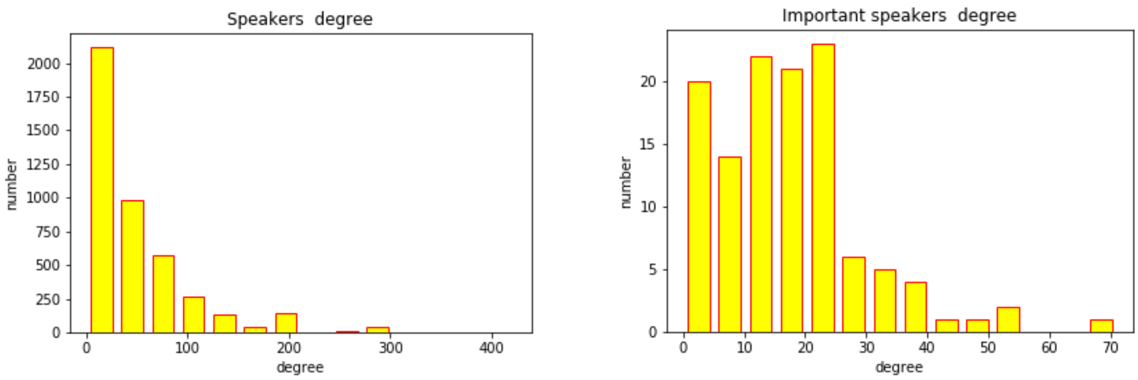

Figure 21: Degree distributions of networks 1 and 2

Both networks seem efficient in spreading information. The two networks have in common a high degree of grouping of actors, due to meetings in groups and within institutions. Because of the "small world effect", the information will need to travel more on average to reach a person in network 1 than in network 2. Nevertheless, this observation on the structure is mitigated by inequality in the number of connections in both graphs: highly connected people are more important in network 1 than in network 2. This way, the low level of connectivity in network 1 can be compensated by choosing the right people at strategical places to spread information.

4.2.3.2 Communities

We now consider the modularity classes given by the modularity detection algorithm. We focus on 3 main classes. Analysing Figure 22 below, we observe that at the left, in green, there is a subnetwork of events with an international range. These people contribute to diplomatic events aiming to create cooperation and action in the different states worldwide. At the bottom, in blue, are events from international organisations promoting about policy and regulation. At the right, in purple, we identify conferences for local actors. We can conclude that we have moved from a differentiation in terms of conferences to a differentiation in terms of scale of action. It is false to consider that there is a network of policymakers, a network of scientists and a network of lobbyists. Each sub-network has in various proportions each type of actor, itself being explainable by the purpose of the event. Also, and importantly, the main policymakers (in the middle of the graph) tend to navigate between the three scales of action we identified.

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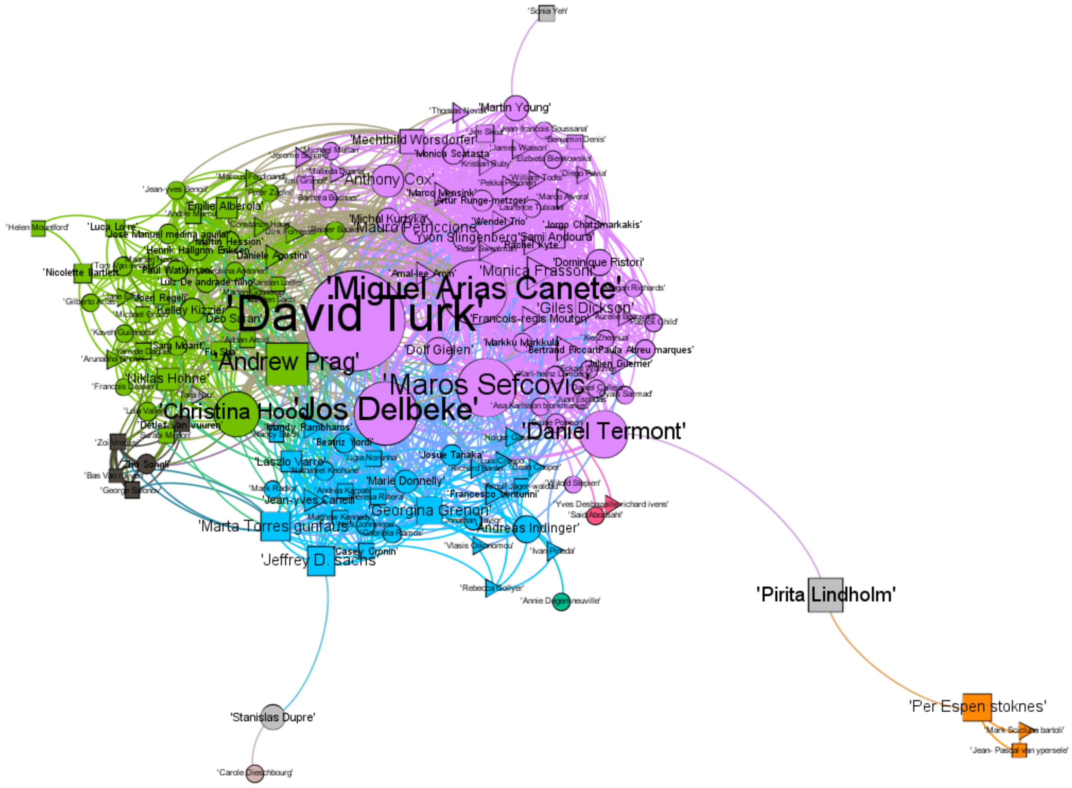

Figure 22: The modularity classes in network 2

Note: Each dot represents an individual and the colour of each individual is defined by the modularity class of which they are part of. Furthermore, the geometric shape of the dot is indicative of the person being, an expert (square), a policymaker (circle), or a lobbyist (triangle).

From the community analysis of the network of important speakers we observe that individuals are classified not by their category but rather by the overarching theme of the conferences they participate in. As such we identify three main themes: global climate diplomacy (green), global technical conferences on climate policy (blue), and local technical conferences on climate policy in the EU (purple).

4.2.3.3 Centrality

We measure betweenness centralities, considering categories as one actor. This allows comparing policymakers, experts and lobbyist in both graphs. Regardless of the measure and network, policymakers are the most central actors of the network. While this is not surprising, there are still many interesting comparisons to make between experts and lobbyists. In network 1, for which the results are displayed in Table 15, lobbyists are individually more central but as a group less central than experts. That means that while lobbyists are individually influent, their influence is redundant as a group. Also, we see that experts are on average more influent than lobbyists but less numerous. In network 2, for which the results are displayed in Table 16, experts are more influential than lobbyists on every measure. In this network, there are proportionally less lobbyists. A list of the 10 most central individuals based on closeness centrality is included in Annex 5.3.

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Table 15: Betweenness centralities of network 1

Network 1	Group centrality	Group centrality normalised	Sum of individual centralities	Normalised sum	Mean of individual centralities	Normalised mean
Policymakers	2,850,883.4	0.54	13,550,164.2	0.63	11,198.5	1.94
Experts	1,386,105.2	0.26	3,579,473.2	0.16	3,795.8	0.49
Lobbyists	1,047,803.7	0.20	4,546,771.5	0.21	2,840.0	0.66
*mean global centrality: 5,774.2						

Table 16: Betweenness centralities of network 2

Network 2	Group centrality	Group centrality normalised	Sum of individual centralities	Normalised sum	Mean of individual centralities	Normalised mean
Policymakers	1,979.1	0.48	7,957.7	0.59	122.4	1.32
Experts	1,378.2	0.33	3,666.9	0.27	96.5	1.04
Lobbyists	788.8	0.19	1,857.9	0.14	44.2	0.48
*mean global centrality: 93.0						

Policymakers are the most important members of both networks in terms of building bridges between different communities. Meaning that in network 1, where the communities are defined by institutions, policymakers create links between institutions and, in network 2, between overarching topics.

We also observe that experts are individually less important, but globally more important than lobbyists. The reason for this finding is that according to our sample they participate in a greater variety of events from different institutions/DGs compared with lobbyists.

4.2.3.4 Homophily

It is meaningful to look individually at what type of actor individuals are confronted. It makes more sense considering such information for important speakers as their motives in one conference is to see other important speakers rather than the rest of speakers (in average of every type). Results are displayed in Table 17. For network 1 we observe a tendency of preferential attachment, given that each group is more connected with their own kind compared with other groups. This trend holds also when considering the proportions each group represents within the network. For instance, in network 1, lobbyists are the most represented group, yet policymakers and experts have little connections with this group. For network 2, there is diversity in the neighbourhood of each type. Each type tends to meet more policymakers, but there is no clear effect. Indeed, as shown by Table 12, given that the proportion of policymakers is higher in network 2, meaning there is no clear evidence of a phenomenon of concentration of lobbyists/experts around policymakers.

Table 17: Share of connections between different categories

Network 1				
From/to	**Policymakers**	**Lobbyists**	**Experts**	**N/A**
Policymakers	39.0%	37.6%	23.4%	0.0%
Lobbyists	25.9%	52.1%	21.9%	0.1%
Experts	29.5%	40.0%	30.5%	0.0%

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Network 2				
From/to	**Policymakers**	**Lobbyists**	**Experts**	
Policymakers	52.5%	27.4%	20.0%	0.1%
Lobbyists	49.5%	32.6%	17.8%	0.1%
Experts	48.1%	23.6%	28.1%	0.2%

4.2.4 Analysis of the events network

The analysis of the network of events provides understanding on how the data is structured. It also gives insights on the way themes are linked.

4.2.4.1 Connectivity

If we investigate large, connected components we find that 21% of the events are out of our main connected component. When we examine these events, some of them are on very specific topics. For others, it is often small events. We identify two possible explanations for the above: first, there is no connection between the topics of the events; second, and most likely, they are linked to the main component through other events that were not available online.

In the events network, the average number of speakers is 19, the average degree is 9.8 and, in each event, an average of 3.5 persons participate in other events. Thus, a small number of people are responsible for most of the links. The coefficient of variation, amounting to 0.99 is high. It means that a few conferences contain many high-level speakers. These are conferences from the EU and the IEA taking a global approach; it appears that these conferences are best suited to convey ideas. The degree distribution represented in Figure 23 shows that most events have a degree lower than 20 while a few highly connected events display degree up to 60.

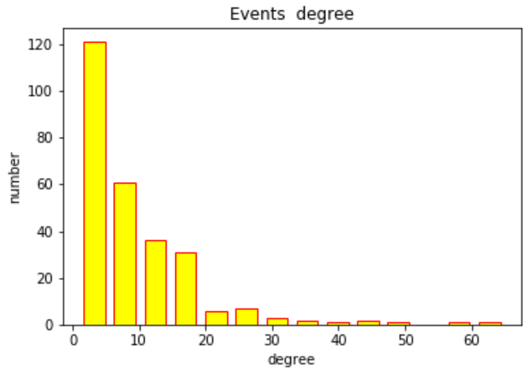

Figure 23: Degree distribution of the events network

Note: degree stands for the number of connections with other events a given event has. The Y-axis in this case refers to number of events that have a given degree.

While some EU events (COP side events) were cut in subevents between days, other IEA events on few days were kept as one. It was a subjective choice that makes IEA events longer than the average, and so having a higher degree. Although the size of events has some influence, it is still very interesting to look into the details displayed in Table 18.

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Table 18: Events ranked by degree, 20 most central events

Event	Institution	degree
The EU vision for a modern, clean and competitive economy	European Union	57
COP23/CMP13/CMA2: 23rd Session of the Conference of the Parties	UNFCCC	49
Conference on International Carbon Markets	European Union	46
IEA Renewables Policies Post-COP21 Workshop	IEA	43
Talanoa dialogue (EU)	European Union	38
European Union Energy day	IEA	34
COP23 Bonn Side events group: 19	European Union	33
COP22/CMP12/CMA1	UNFCCC	32
2017 Global Forum on the Environment and Climate Change	OECD	31
18thI EA-IETA-EPRI Annual Workshop on Greenhouse Gas Emission Trading	IEA	31
EU Covenant of Mayors Ceremony	European Union	28
2018 Global Forum on the Environment and Climate Change	OECD	27
EU ETS revision expert meeting: Outlook on the correction factor in phase 4	European Union	27
COP24 Side events group: 29	European Union	26
COP21 technical day	IEA	25
High Level Round Table on Low-Carbon Innovation	European Union	25
Financing energy efficiency in Central and South Eastern Europe	European Union technical	24
Platform for Coal Regions in Transition 5th working group	European Union technical	23
FINANCING ENERGY EFFICIENCY IN CENTRAL EUROPE	European Union technical	22

Events in the network are connected through the participants they have in common; we notice that in general a small number of participants are responsible for creating most connections between events. Since only some events have a large number of connections to other events we conclude that important participants only attend a limited number of important events in our sample.

We used a modularity optimisation algorithm to constitute the groups presented in Figure 24. When considering the events in the groups returned by the modularity algorithm, we observe that these groups match with different themes. The blue block (173 events) is roughly about high-level climate policy. The black block (43 events) contains nearly exclusively events about energy efficiency. Finally, the purple block (38 events) tackles industrial matters with 3 main topics: coal sector transition, sectorial innovation funds and the carbon market (ETS).

According to our analysis, each group is very isolated because there are only 30 cross-group edges (out of 1,250). These connections are the reflection of 14 persons.

We see that this phenomenon is correlated with the DGs organisation in the EU. To illustrate the phenomenon, in Figure 20 we see that the events from the right top corner block are organised by DG ENERGY. It is interesting to underline the very few links between DG CLIMA and DG ENER while the two DGs are under the same Commissioner. Miguel Arias Cañete, Commissioner for Energy and Climate from 2014 to 2019 surprisingly does not link the blocks. The reflections suggest a compartmentalisation of the themes in the EU. We are cautious in drawing strong conclusions due to the fact that our sample covers roughly 15% of all EU conferences.

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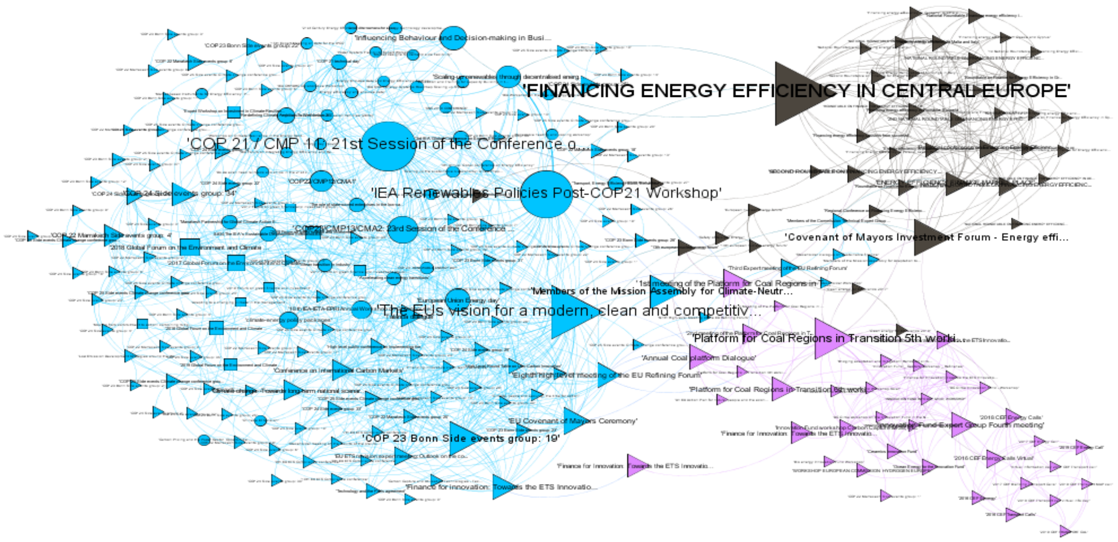

Figure 24: The events divided into modularity groups

Note: Colours depict the different modularity classes and shapes the organiser of the event. As such, triangles are EU events, circles IEA events and squares OECD events.

To confirm the point we make above, we built a homophily table (Table 19). The table should be read by columns (e.g. 7.6% of IEA events' links are from OECD, reciprocally 29.4% of IEA events' links are from OECD). We first notice that as we specialize our analysis, we tend to have granular and imprecise tendencies. Two distinct groups in EU conferences come out, macro and governance events (DGs CLIMA, DG REGION, EEAS) and technical events (DGs ENER/RESEARCH/ENVIRONMENT/FISMA). The main structures (IEA, OCDE, DG CLIMA, DG ENER) are quite independent as testify the high diagonal values. Surprisingly, the DG ENER and the IEA do not communicate much. It seems that the IEA plays a role like DG CLIMA in talking to global actors, while the DG ENER takes a more technical participation. An interesting point would be to know if large amounts of internal communication exists between DG ENER and CLIMA. It must be noted however that there are some biases in these stats due to the number of participants to each event, and the total number of events in each structure.

Table 19: Homophily between different DGs/Institutions

%	IEA	OCDE	DG CLIMA	DG ENER	DG REGIO	INEA	EEAS	DG RESEARCH	DG ENVIRON-MENT	DG FISMA
IEA	63.4	29.4	14.0	3.8	13.3	NaN	13,3	NaN	NaN	NaN
OECD	7,6	26.1	6.1	0.7	NaN	NaN	NaN	NaN	NaN	NaN
DG CLIMA	24.5	41.8	71.0	10.6	60.0	4.9	66,7	0.182	NaN	NaN
DG ENER	3.5	2.6	5.6	80.9	20.0	4.9	13.3	54.5	100.0	42.9
DG REGIO	0.7	NaN	1.7	1.1	NaN	NaN	6,7	0.091	NaN	NaN
INEA	NaN	NaN	0.4	0.7	NaN	90.2	NaN	NaN	NaN	NaN
EEAS	0.3	NaN	1.0	0.4	3.3	NaN	NaN	NaN	NaN	NaN
DG RESEARCH	NaN	NaN	0.2	1.1	3.3	NaN	NaN	NaN	NaN	28.6
DG ENVIRON-MENT	NaN	NaN	NaN	0.4	NaN	NaN	NaN	NaN	NaN	NaN
DG FISMA	NaN	NaN	NaN	0.5	NaN	NaN	NaN	0.182	NaN	28.6

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From the table we see that IEA and OECD events are closer to EU global events than EU technical events. A hypothesis to explain that would be that the first conferences are focused on general matters, while the second is about concrete implementation.

When identifying communities within the events network, the classification reflects different themes that are closely linked with institutions and DGs. Indeed, the blue block reflects events that deal with question of high-level climate policy, the black block with energy efficiency and the purple block with industrial matters.

According to our sample we note that, whilst the EU deals with all 3 types of events, the IEA and OECD only organise high-level climate policy events.

4.2.5 Conclusion

The first network with all speakers presents a global view of our dataset. It contains all actors and the links between them. In terms of communication, this network was unequal, due in part to the lack of data (1 conference out of 6) but also to theme separations, and inequalities between speakers. The structure of the debate in the first network is oriented on the structure of the events, with few speakers on different topics. Concerning the actors, we see that individual effects are different from group effects. Even if experts are individually less influential than lobbyists, we see that they communicate much more as a group. That means that lobbyists tend to aggregate on a few conferences, while experts are more spread. Thus, we expect the experts have more impact because they do not enter in competition.

The second network with cross-institutional speakers is useful to tackle issues concerning communications between institutions. Also, as it deletes the aggregation bias caused by people attending only one conference, this network contains a higher proportion of international speakers. This network is much more equal than the global one. We believe it is representative of global negotiations, and we see that European politicians are central. When detecting communities, this time, rather than themes, we see emerging scales of debate. We identify three categories of conferences: on climate negotiations, on global implementations, and on regional implementation. Each category has different proportions of experts/policymakers/lobbyists.

Concerning the actors, our main finding is that experts are, like policymakers, involved at different levels of negotiation. The lobbyists are mainly present in global negotiations and global implementation discussions.

The last network is the network of events. It provides a better understanding of the links between topics, DGs of the EU Commission and institutions. The links between events present a difference between EU macro events, which are well connected, and EU technical events, which tend to be isolated from one another. On local implementation events, the topics are separated and do not communicate together or with the global debate. Applied to Europe, it means DG CLIMA and DG ENER do not communicate much. This is surprising given that those two DGs were united behind Miguel Arias Cañete. It may be the case that most of the communication is internal and not accessible to us.

The structure reveals that the DGs are not well connected by events. The most central events are global Forums/COP where negotiations are held. The IEA and OECD events are closer to EU global events than EU technical events.

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5 ANNEX

5.1 Key words used to classify stakeholder database entries

individual words

firms = 'journalism journalist business finance production engineer engineering bank operators newspaper news incorportated producer company enterprise firm corporation consulting consultancy supplier conglomerate private multinational corporate'

research ='campuses institute school postgraduate graduate think tank academy academic research university student education'

assocs = 'advocacy federation partnership society network forum charity endowment association non-for-profit non-governmental organization NGO foundation non-profit'

govs = ' legislative region central institution institutions department government governments ministry Republic governmental intergovernmental agency public Directorate-General Minister'

others = 'establishement entity center established'

#bigrams

assocs_b = 'non-governmental organisation industry association business organization Chamber of Commerce'.split()

govs_b = ' intergovernmental economic organisation European Parliament central bank central banking international organization international organizations diplomatic mission world government department'.split()

firms_b ='credit rating investment bank financial services news agency asset management services company public relations marketing company'.split()

types of firms

energies ='energy electricity fuel oil gas wind solar power electric'

bankings ='banking finance insurance bank financial'

consultings = 'services consultancy attorney Attorney law consulting accountant accounting PR marketing advisor'

manufacturings = 'conglomerat conglomeration industry industrial manufacturing construction assembling robotics building manufacturer engine car '

chemicals = 'chemical chemicals healthcare pharmaceutical drugs chemistry'

presss = 'news press newspaper media'

ICTs = 'telecom telecommunications telecommuniations technology software ICT broadband telephony television computer computers electronics telephone'

#bigrams

en_b =bigram('energy company utilities company electricity provider grid operator energy producer power

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company'.split())

bank_b=bigram('financial services banking group credit rating investment bank asset management insurance company'.split())

consult_b = bigram('professional services consulting company public affairs law firm accounting firm public relations'.split())

manu_b = bigram('conglomerate company industrial manufacturing automation technology automotive corporation heavy electrical equipment rail transport'.split())

chem_b =bigram('chemical company pharamaceutical company copper producer'.split())

press_b = bigram('news agency news magazine daily newspaper'.split())

ICT_b =bigram('technology company telecommunications company internet provider'.split())

types of NGOs

associations = 'association industry federation advocacy forum Chamber of Commerce'

foundations = 'foundation charity endowment non-for-profit non-profit society non-governmental NGO'

types of government

nationals = 'national regional government sovereign country ministry'

europeans = 'european EU europe international organizations organization'

types of academic institutions

universities = 'university postgraduate graduate student education campus'

institutes = 'think tank institute academy research'

5.2 Most central individuals in the Twitter networks

Followers network				
Name	Category	Betweenness ranking	Degree ranking	Closeness ranking
Simon Evans	Press	1	1	27
Jesse Jenkins	Expert	2	4	7
Miguel Arias Canete	Policy maker	3	39	219
Ed Crooks	Private	4	5	11
Greta Thunberg	Private	5	19	510
Leo Hickman	Press	6	2	14

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Barack Obama	Private	7	95	814
Mark Johnston	Private	8	46	116
Saleemul Huq	Expert	9	3	2
Kees van der Leun	Private	10	28	153
Adam Vaughan	Press	11	12	52
Ryan Heath	Press	12	161	220
Eric Holthaus	Press	13	8	22
Will Yeates	Private	14	6	10
Joe Nyangon	Expert	15	10	6
Andrew Revkin	Expert	16	16	96
Karl Mathiesen	Press	17	11	13
Sebastien Duyck□	Private	18	9	5
Natalie Bennett	Policy maker	19	45	24
Chris Littlecott	Expert	20	7	4
Tweets network				
Name	Category	Betweenness ranking	Degree ranking	Closeness ranking
Simon Evans	Press	1	1	22
Michael Liebreich	Private	2	4	74
Greta Thunberg	Private	3	2	659
Kees van der Leun	Private	4	12	279
Zeke Hausfather	Expert	5	3	169
Glen Peters	Expert	6	6	223
Andreas Graf	Expert	7	34	12
James Murray	Press	8	10	248

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Frans Timmermans	Policy maker	9	7	715
Oliver Geden	Expert	10	30	16
Mark Johnston	Private	11	47	13
Kevin Anderson	Expert	12	73	116
Rachel Kyte	Expert	13	21	99
Teresa Ribera	Policy maker	14	48	207
LisaFischer	Expert	15	56	14
Jean-Michel Glachant	Expert	16	91	249
Laurence Tubiana	Expert	17	46	79
Dave Jones	Private	18	24	9
Fatih Birol	Policy maker	19	8	618
Michael E. Mann	Expert	20	18	601

5.3 Most central individuals in the key persons network based on closeness centrality

Top 10 closeness centrality	Function	Type	Reduced degree	Global degree
David Turk	Acting Director for the Sustainability, Technology and Outlooks Directorate International Energy Agency,	P	71	409
Jos Delbeke	Director General for Climate Action, European Commission (2010 - 2018)	P	53	412
Miguel Arias Cañete	Climate Action and Energy Commissioner (2014 - 2019)	P	52	298
Christina Hood	Head of Environment and Climate Change Unit, IEA	P	47	277

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Andrew Prag	IEA, on behalf of the OECD-IEA Climate Change Expert Group	E	42	270
Dolf Gielen	Director, International Renewable Energy Agency IRENA	P	36	177
Georgina Grenon	Director, 100 % Renewable Energy Solutions, ENGIE and Vice Chair, IEA	E	36	423
Maros Stefcovic	Former Vice-President for the Energy Union, European Commission	P	35	257
Marie Donnelly	European Commission Director, New and Renewable Sources of Energy	P	32	255
Mandy Rambharos	Climate Change and Sustainability Manager, Eskom	L	31	146

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