Analyzing the dynamics of innovation networks in climate technologies

Malte Toetzke[a,c,b,*], Benedict S. Probst[c,b,f], Stefan Feuerriegel[d,e], Laura Diaz Anadón[f,g], Volker H. Hoffmann[b]

[a]*TU Munich, Munich, Germany*
[b]*ETH Zurich, Zurich, Switzerland*
[c]*Max Planck Institute for Innovation and Competition, Munich, Germany*
[d]*LMU Munich, Munich, Germany*
[e]*Munich Center for Machine Learning, Munich, Germany*
[f]*University of Cambridge, Cambridge, United Kingdom*
[g]*Harvard University, Cambridge, United States*

Abstract

Innovation networks are essential for the development, commercialization, and adoption of climate technologies, yet their structure and dynamics remain poorly understood. To address this gap, we use large language models on 26 million LinkedIn posts to map a global network of 166,459 organizations and 442,250 collaborations ($\sim$1.4 million direct partnerships) across 189 countries. Our dataset spans 27 climate technologies and 17 collaboration types, including demonstration projects, product launches, adoption, and equity investments. We find that, between 2020 and 2024, governmental organizations became increasingly central in these networks, with two key implications: On the one hand, increases in the centrality of governmental organizations are associated with substantial expansions in the overall numbers of domestic partnerships, which points to a catalyzing role of the public sector for domestic industrial ecosystem formation in climate-tech. On the other hand, increased governmental centrality also creates a high dependence on governmental involvement. In the period between 06.2022

*Corresponding author.
Email address: malte.toetzke@tum.de (Malte Toetzke)

and 12.2024, 62% of all global partnerships in climate-tech innovation networks depended on government involvement. This dependence raises concerns about the resilience of climate-tech innovation networks to shifting political and fiscal priorities. Finally, we find that, compared to the United States, innovation networks in the European Union exhibit less cross-regional partnerships and technological specialization, which may constrain industrial competitiveness. Our machine learning approach provides a scalable methodology for continuously tracking innovation networks, with broad applications for industrial analysis and policy evaluation beyond climate technologies.

Keywords:
Machine learning, large language models, innovation networks, LinkedIn,
climate technologies, industrial policy

---

1. Main

Achieving net-zero emissions hinges on the rapid advances of climate technologies (climate-tech) from development to commercialization and large-scale adoption of mature technologies. Although emerging industries in climate-tech hold considerable economic promise [1, 2], many technologies remain in early stages between development and commercialization, or lack the scale necessary for widespread market adoption [3]. In response, countries worldwide have implemented ambitious green industrial policies (GIPs) to spur climate-tech innovation and bolster domestic leadership in emerging industries, such as the United States (US) Inflation Reduction Act (IRA) [4] and the European Union (EU) Net Zero Industry Act [5].

Climate technologies are developed, commercialized, and scaled through innovation networks that connect diverse actors, such as universities, startups, incumbent firms, financial institutions, and governmental organizations [6, 7, 8]. These networks catalyze innovation by facilitating access to complementary resources and capabilities [9, 10, 11] and enabling knowledge spillovers, which are crucial for technological refinement and scale-up [12, 13, 14, 15]. Existing studies on climate-tech innovation focus primarily on early-stage invention (e.g., via publications and patents) [16, 17, 18, 19] and late diffusion stages (e.g., via trade and deployment indicators) [20, 21, 22, 23]—despite the importance of the middle stages in the innovation process (spanning demonstration, commercialization, and early adoption), where many ventures and organizations fail due to insufficient financial capital, infrastructure, market demand, or viable business models [24, 25, 26, 27]. Yet, there is a lack of comprehensive data that capture the entire innovation process across all innovation stages [11, 28].

To address this gap, we develop a machine learning approach that maps climate-tech innovation networks by analyzing 26 million LinkedIn posts from key public and private organizations. Our machine learning approach constructs the network of organizations and climate-tech collaborations in two main steps (Figure 1a): First, we use large language models (LLMs)

to classify the LinkedIn profiles of organizations into 18 organization types (e.g., universities, manufacturers, venture capital firms; Supplementary Table S13) and 46 sectors (e.g., automotive, chemicals, software; Supplementary Table S14). Second, we apply LLMs to (1) identify announcements of climate-tech innovation collaborations from the LinkedIn posts of organizations; (2) classify these announcements into 17 collaboration types (e.g., research and development, demonstrations and pilots, product launches, equity investments; Supplementary Table S17) and 27 climate technologies (e.g., offshore wind, electric vehicles, direct air capture; Supplementary Table S18); and (3) extract collaborating organizations from the posts. We performed these steps over three iterations, starting with an initial set of organizations from Bloomberg New Energy Finance (BNEF) [29] and expanding the network by adding new organizations that were identified through collaborations in the previous iterations (details are provided in the Methods section). Our machine learning approach enables systematic and large-scale retrieval of innovation collaborations across the entire innovation process and with continuous updates over time.

Our final dataset comprises 442,250 innovation collaborations between 166,459 organizations, representing $\sim$1.4 million direct partnerships. As multi-actor collaborations connect more than two organizations, we transform all collaborations into direct links between organizations, hereafter called "partnerships" (Supplementary Figure S4; details are described under *Network graph* in the Methods). Collectively, the included organizations operate from 345,479 locations across 189 countries (Figure 1b) and employ around 136 million people (based on reported employment of LinkedIn members; Supplementary Figure S5). The dataset spans collaborations from January 2017 to December 2024. While our approach aims to track global collaborations, it is likely that organizations and collaborations from China, Korea, and Japan are underrepresented due to lower LinkedIn activity in these countries (we analyze and discuss our coverage across countries and organization characteristics in the Supplementary Discussion S1). How-

ever, our data show high representativeness across different sectors, organization sizes, and organizational maturity (see Supplementary Discussion S2 and S3). Finally, our data allow us to track changes in climate-tech innovation networks over time and across a wide range of technologies, geographies, and innovation activities, shedding light on the critical transition from lab-scale research to large-scale diffusion.

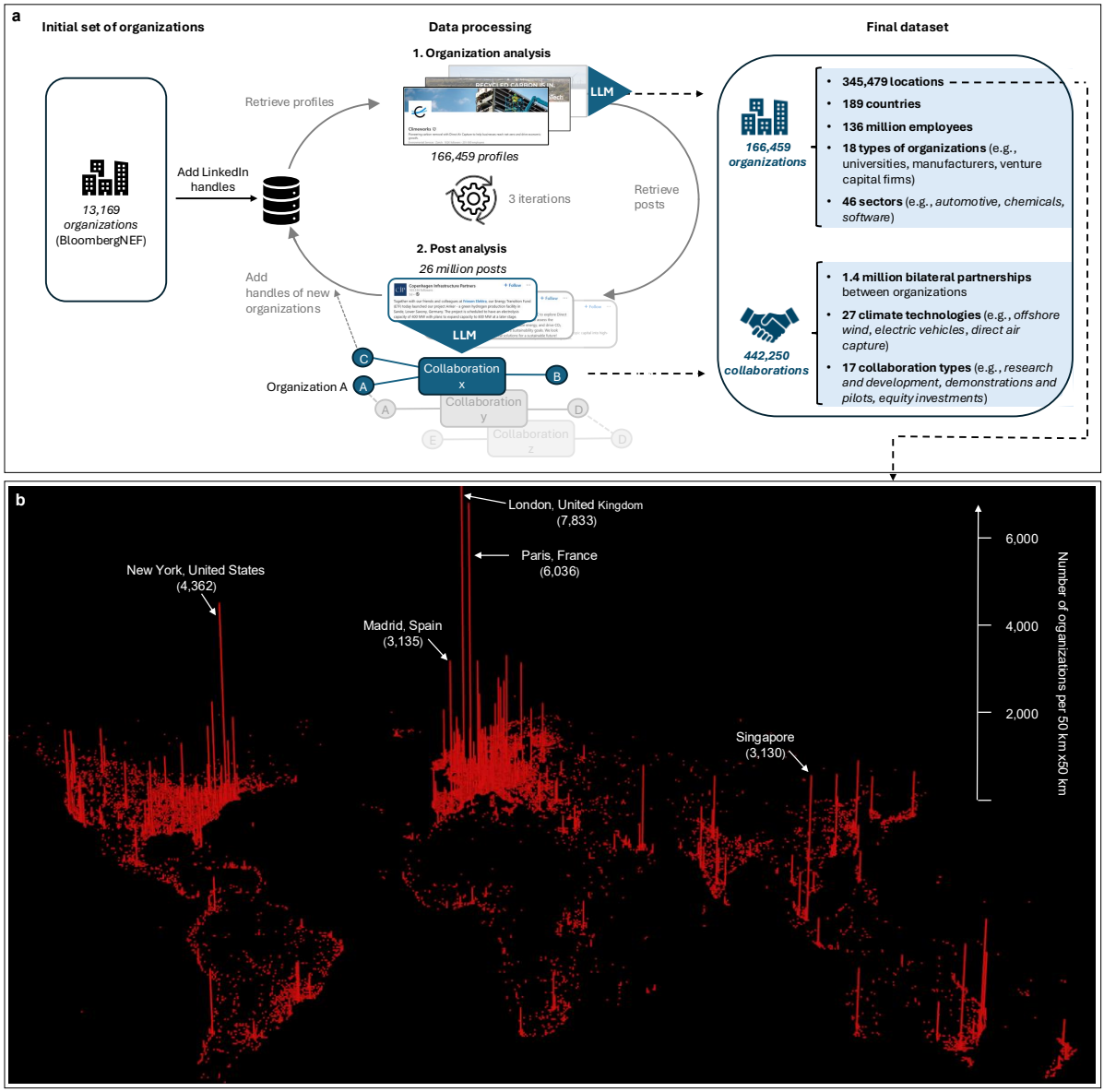


Figure 1: **Overview of the machine learning approach and final dataset capturing innovation collaborations in climate-tech. a,** Overview of information retrieval process and final dataset spanning collaborations from 01.2017–12.2024. Note that collaborations can include multiple organizations, which results in a higher number of bilateral partnerships (see Supplementary Figure S4). **b,** Geographic distribution of organizations engaging in climate-tech collaborations as of January 2025, based on 50 km x 50 km grids.

2. Evolution of global innovation networks across different climate-techs

Structures and activities in climate-tech innovation networks are evolving dynamically. To compare innovation networks over time, we use the enactment of the Inflation Reduction Act (IRA) in July 2022 [4] to distinguish between two time periods of equal length: the Pre-IRA (01.2020–06.2022) and the Post-IRA period (07.2022–12.2024). Between the periods, our data show a substantial expansion of innovation networks across technologies, with an overall increase of 93% in the number of newly formed partnerships and 49% in the number of participating organizations (Figure 2; Supplementary Table S15). Percentage increases in the number of organizations and partnerships are highest for technologies in the commercialization stages (e.g., direct air capture, bioenergy with carbon capture and storage, sustainable aviation fuels), but seem to decrease along market uptake and large-scale diffusion.

In the following, we discuss the structure and dynamics of innovation networks for three exemplary climate-techs, namely, (i) nuclear fusion, (ii) direct air capture, and (iii) green hydrogen (Figure 2; a definition of the scope of the technology categories is provided in the Supplementary Table S18). These technologies represent different development stages, from nascent technologies (technology readiness level (TRL): 1–3; e.g., nuclear fusion) that are in the early stages of technological development; to emerging technologies (TRL: 4–7; e.g., direct air capture) that are entering the market with first commercial deployment; and scaling technologies (TRL 8–9; e.g., green hydrogen) that are experiencing increased uptake in manufacturing and deployment [30].

For nuclear fusion, we observe how progress in demonstration and pilot projects in the Pre-IRA period has catalyzed a substantial expansion in research and development (R&D) partnerships, while initiating first commercialization efforts. During the Pre-IRA period (01.2020–06.2022), the innovation network was primarily shaped by the construction of large demonstration reactors (Figure 2a), such as ITER in France [31] and SPARC in the United States [32].

Consequently, partnerships during this period were dominated by demonstrations and pilots (n=623 partnerships), with the international research organization ITER emerging as a central actor, connecting 89 manufacturing organizations (primarily conductor material producers, such as ASG Superconductors and Elytt Energy), project management (e.g., Assystem), and governments (e.g., the Italian National Agency for New Technologies, Energy and Sustainable Economic Development (ENEA), United Kingdom Atomic Energy Authority). In the Post-IRA period (07.2022–12.2024), the number of partnerships around demonstration projects remained stable, which reflects the long development timelines. However, we observe two major shifts: first, R&D partnerships surged by 491% (n=2,222), likely driven by research breakthroughs at existing demonstration plants (e.g., the National Ignition Facility (US), Joint European Torus (UK), Wendelstein 7-X (Germany)). Second, initial commercialization partnerships emerged (n=98), accompanied by the entry of venture capital firms and the first recorded offtake agreements (n=7), which commit to purchasing future electricity supply from Helion's planned first-of-its-kind fusion power plant in the United States (expected to launch in 2028). These trends suggest that technological milestones in nascent technologies stimulate intensified R&D activity while facilitating the transition to commercialization, a phenomenon that underscores the non-linear nature of technological innovation [33].

For direct air capture (DAC), we observe the emergence of foundational industrial structures, which appear to be substantially driven by the US Department of Energy (DOE). During the Pre-IRA period (01.2020–06.2022), the DAC innovation network was highly concentrated around two core technology manufacturers: Climeworks (degree centrality=86) and Carbon Engineering (45; Fig 2b), supported primarily by venture capital firms, such as Breakthrough Energy (28), and by the US DOE (28). In the Post-IRA period (07.2022–12.2024), the network expanded substantially. This includes the emergence of new DAC manufacturers as central actors (e.g., Heirloom (60), Capture6 (56)). At the same time, DAC manufacturers increas-

ingly formed partnerships with a broader range of organizations, including early adopters (e.g., Stripe, Milkywire, Shopify) and complementary service providers (e.g., PuroEarth, Carbon Direct), which facilitate the monetization of DAC plants via carbon credit markets. In addition, the US DOE moved to the center of the innovation network (from degree centrality 28 to 109), particularly due to supporting the formation of direct air capture hubs through a USD 3.5 billion bill [34]. Between the two periods, partnerships focused on first commercial deployments increased by a factor of 15 (from 26 to 425). The evolution in the DAC network highlights the critical role of early movers (e.g., Climeworks, Breakthrough Energy, US DOE) in enabling technological advancement and mobilizing a broader ecosystem of adopters, service providers, and emerging competitors toward commercialization.

For green hydrogen, innovation partnerships expanded across all innovation stages between the two periods – from R&D to operations and maintenance. The strongest relative increase occurred in offtake agreements, which reflects a growing emphasis by industrial firms on securing future supply in the emerging green hydrogen markets. Unlike nascent and emerging technologies, where centrality dynamically shifts between types of organizations, the green hydrogen innovation network remained structurally stable at the level of organization types, with changes in centrality primarily occurring at the level of individual organizations. This observation suggests that, by the Pre-IRA period (01.2020–06.2022), the sector had already developed a mature industrial structure, which was subsequently scaled through an expansion in project activity in the Post-IRA period (07.2022–12.2024). Incumbent manufacturers from adjacent industries, such as Siemens Energy, Air Liquide, and Shell, occupy central positions in this network. Their increasing engagement illustrates how established firms intensify investments as the commercial viability of specific applications of green hydrogen becomes clear [35]. The broad involvement of incumbents across sectors (e.g., Airbus, Shell, Thyssenkrupp) further underscores the complementary nature of green hydrogen, with potential applications spanning

industrial decarbonization, seasonal energy storage, and aviation. More broadly, these findings highlight that, in scaling technologies, network expansion is driven less by the entry of new organizational types and more by the deepened participation of established industrial actors integrating the technology into their core operations.

Across climate-techs, we observe different geographical dynamics of innovation networks, which depend on their stage of innovation. The share of domestic partnerships has increased for nascent and emerging technologies over the two periods, while it has decreased for scaling and mature technologies (Supplementary Table S19). An exception to this trend is biochar and bioenergy with carbon capture and storage (BECCS), which have become more international despite still being in early development stages. This deviation likely stems from the decoupling of physical and digital value creation of carbon removals, where carbon credits generated in a specific region can be digitally traded anywhere in the world. The shift toward nationalized networks in earlier stages reflects a transition from highly international research collaborations to more localized partnerships that support demonstration, first deployments, and early adoption and where geographical proximity enhances trust [36] and knowledge exchange [37, 13]. In contrast, in scaling and mature technologies, innovation networks become more international as organizations and value chains expand into new markets, thereby increasing the global diffusion of technologies and components, operations, and knowledge [38, 13].

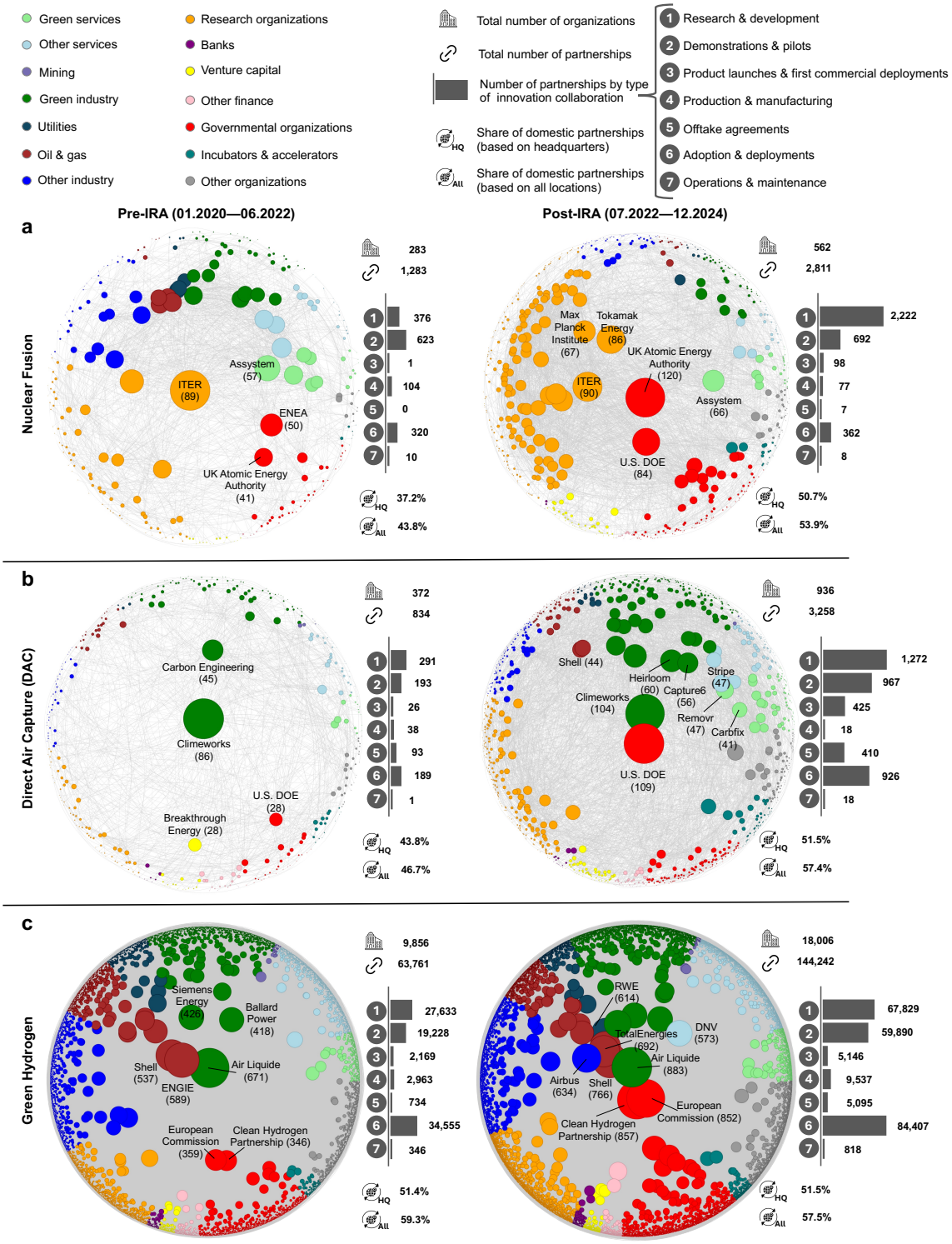


Figure 2: **Structural evolution of global innovation networks across climate technologies.** Shown are two periods before the Inflation Reduction Act (IRA) (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) for **(a)** nuclear fusion, **(b)** direct air capture (DAC), and **(c)** green hydrogen. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called "partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. Node colors correspond to different groups of organizations. To reduce the number of groups, they represent aggregates of underlying organization types (e.g., universities and research institutes are aggregated to *research organizations*, manufacturers and project developers specialized in climate technologies are aggregated to *green industry*; details can be found in the Supplementary Table S16). The horizontal bars show the distribution of partnerships across different types of innovation collaborations. For reasons of space, financial collaborations (e.g., equity investments, loans, grants) and other structural collaborations (e.g., mergers and acquisitions, joint ventures, spin-offs) are omitted from the bar chart. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars, we count partnerships separately for each type of collaboration.

3. Governmental organizations moving towards the center of climate-tech innovation networks

Between the Pre-IRA (01.2020–06.2022) and Post-IRA (07.2022–12.2024) periods, governmental organizations have gained substantial centrality in climate-tech innovation networks. Key governmental institutions, such as the US DOE, the European Commission, and France's Alternative Energies and Atomic Energy Commission (CEA), are now positioned at the center of global innovation networks across most climate technologies (Figure 2; Supplementary Figures S8–S35; other centrality measures besides degree centrality are reported in the Supplementary Tables S28–230). This trend becomes particularly evident for emerging and scaling technologies that require substantial upfront investment for first deployments and infrastructure build-up (e.g., DAC, geothermal energy, green hydrogen). In contrast, for technologies that integrate into existing technologies, infrastructure, and business models (e.g., sustainable aviation fuels, carbon capture and storage, biofuels), centrality remains concentrated among incumbent manufacturers, utilities, and oil and gas majors. These patterns suggest that governmental organizations increasingly play an orchestrating role in climate-tech innovation, stepping in where market uncertainty and investment risk deter private sector leadership.

Our data indicate that increased governmental involvement is strongly associated with an overall expansion of domestic innovation ecosystems. Across all climate technologies, regression analyses show significant positive relationships between increases in governmental centrality and increases in the centrality of domestic organizations overall (Supplementary Discussion S4). Coefficients range from 2.7 (concentrated solar) to 9.2 (battery), which indicates that each additional governmental partnership is linked to several additional domestic partnerships. Furthermore, in 19 of the 27 analyzed technologies, the country that recorded the largest increase in governmental partnerships also experienced the highest overall growth in domestic partnerships (Supplementary Table S20). For instance, in the global DAC network, the US

DOE has increased its innovation partnerships between the two periods and thereby became the most central organization (Figure 2b). This structural shift has been accompanied by a 427% increase in the centrality of US-based organizations in the global network, leading to a global innovation network where 31% of all DAC-related partnerships now take place between US entities, and 56% involve at least one US-based actor. These findings reinforce the notion that governmental organizations not only foster technological progress, but also strategically foster domestic industrial development in emerging climate technologies, for example, by creating market opportunities while lowering investment risks [39].

The high centrality of governmental organizations in climate-tech innovation networks also highlights a broader structural dependency on public-sector involvement. In the Post-IRA period (07.2022–12.2024), 62% of all partnerships depended on governmental organizations, with 28% of partnerships directly involving governmental organizations, while an additional 34% of partnerships arise from multi-actor collaborations that are supported or initiated by governmental organizations (Fig. 3). This marks a four percentage point increase compared to the period from 01.2020–06.2022. This reliance on public-sector participation is not limited to emerging and scaling technologies, where governmental organizations frequently anchor innovation ecosystems, but it is also evident in mature sectors, where they act as providers of infrastructure and regulatory frameworks (e.g., railway, electric nuclear fission, hydro energy).

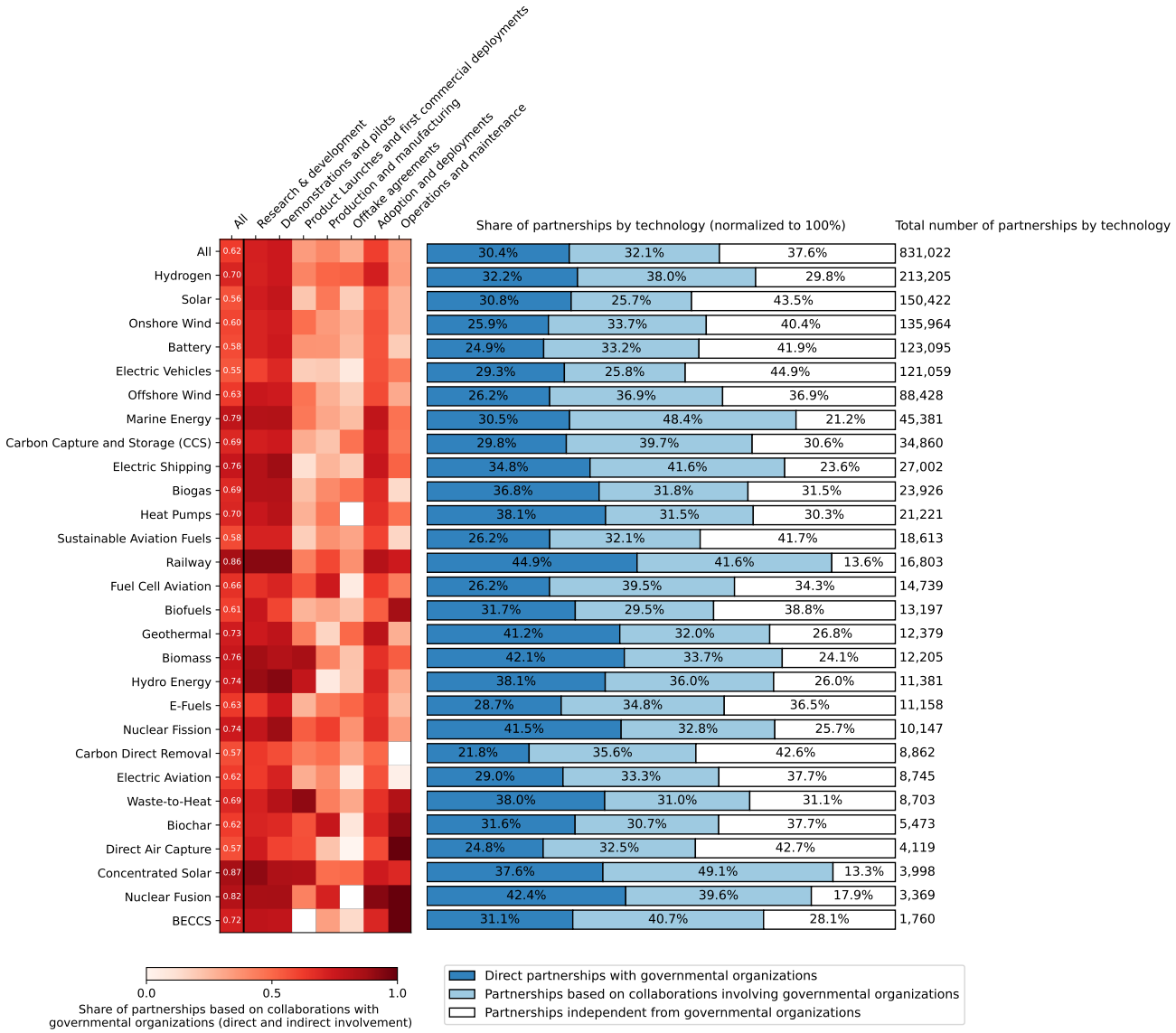


Figure 3: **Indirect and direct involvement of governmental organizations in innovation networks by climate technology and for the Post-IRA period (07.2022–12.2024)**. Direct involvement refers to bilateral partnerships that include governmental organizations. Indirect involvement refers to bilateral partnerships between private sector organizations that originate from larger multi-stakeholder collaborations initiated or supported by governmental organizations. A schematic illustration of direct and indirect involvement of governmental organizations is provided in the Supplementary Figure S36.

4. Divergent structures of climate-tech innovation networks in the EU and the US

The US and EU represent two of the world's largest climate-tech innovation ecosystems and markets. Yet, our comparison shows how the structure of their innovation networks and corresponding governance differ substantially. Our data show that climate-tech innovation networks in the EU show less cross-regional partnerships compared to the US. While in the US, 78.7% of innovation partnerships link organizations from different states (based on headquarter locations of organizations), only 38.3% of partnerships in the EU involve different European countries. Relatedly, we observe low levels of cross-regional specialization, when comparing the number of manufacturers in different climate-techs across EU member countries with few exceptions (e.g., France with a comparatively high concentration of manufacturers in nuclear fission and Denmark with a comparatively high concentration of manufacturers in wind energy (Supplementary Figure S6)). In contrast, US states show large variations in technological specialization including, for example, high manufacturing concentration in batteries and electric vehicles in Michigan, carbon capture and storage (CCS) in Texas, biomass and hydropower in Pennsylvania, and marine energy in Massachusetts (Supplementary Figure S7).

We also observe notable differences in the governance structure of US and EU innovation networks (Figure 4). In the US, innovation networks are highly centralized around the DOE. In contrast, a variety of public institutions at national and European levels occupy central positions in European innovation networks. Examples include the European Commission, the French Agency for Ecological Transition (ADEME), the French Alternative Energies and Atomic Energy Commission (CEA), and the German Federal Ministry for Economics and Climate Action (BMWK). This fragmentation may reinforce geographic clustering within national borders and contribute to the lower degree of cross-regional specialization across EU countries. Similar patterns have been documented in prior studies of European innovation policy [40, 41], which highlight challenges associated with the coordination of multilevel governance structures.

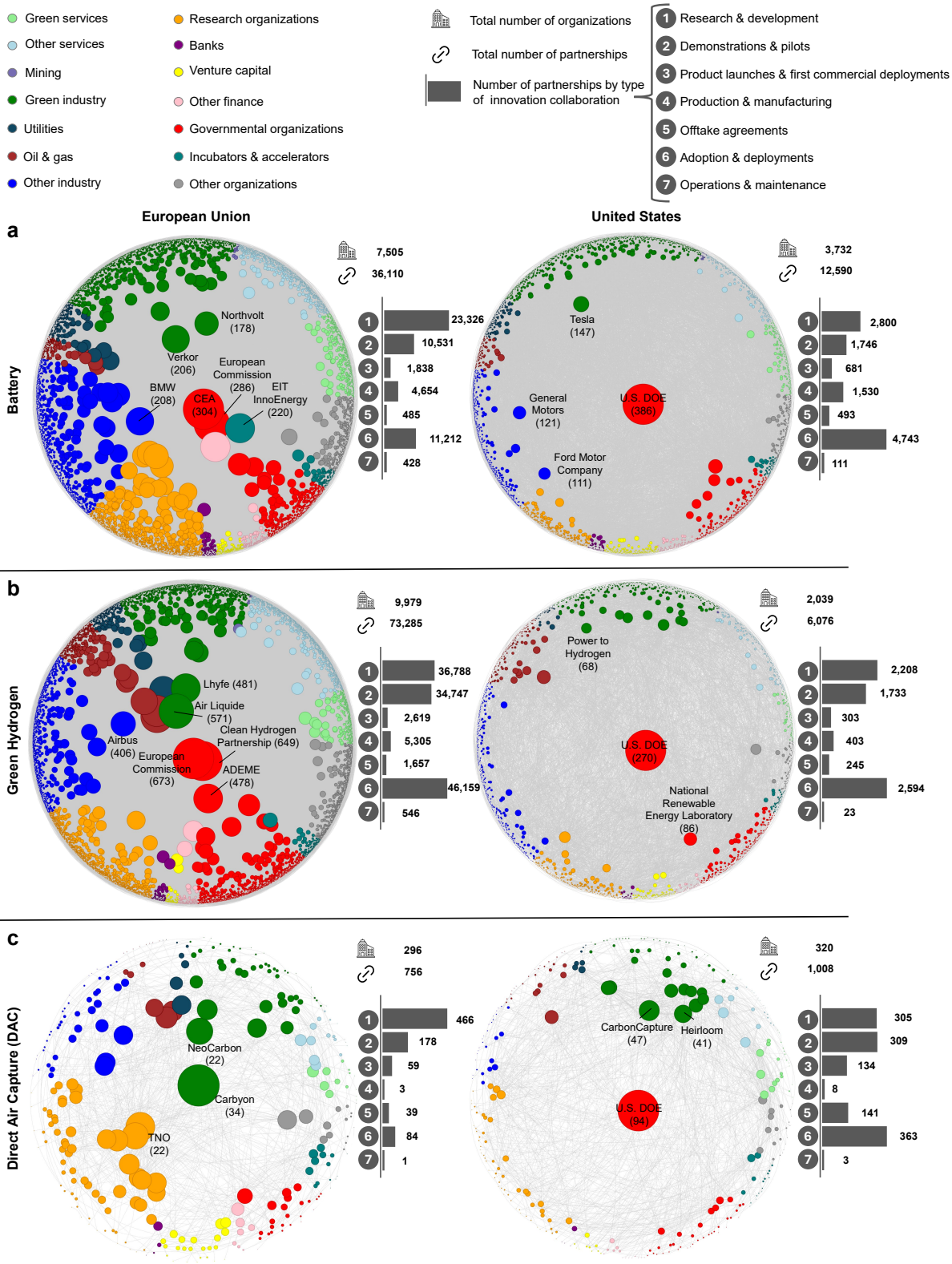


Figure 4: **Structural comparison of climate-tech innovation networks in the US and EU (Post-IRA: 07.2022–12.2024)**. Innovation networks are shown for three exemplary technologies: **(a)** batteries, **(b)** green hydrogen, and **(c)** direct air capture (DAC). The size (radius) of organization nodes represents the degree centrality (number of edges), which is also indicated in brackets for highlighted organizations. Organizations are attributed to different groups of organizations (e.g., "Green services", "Research organizations"), represented by the colors. Some of these groups represent aggregates of underlying organization types (e.g., universities and research institutes are aggregated to research organizations; details can be found in the Supplementary Table S16). Horizontal bars represent the number of links that can be attributed to different types of innovation collaborations. For reasons of space, financial collaborations (e.g., equity investments, loans, grants) and other types of collaborations (e.g., mergers and acquisitions, joint ventures, spin-offs) are omitted in the bar chart. To be included in the domestic network, each partnership needs to involve at least one organization with a headquarter location in the region, whereas the other organization only needs to have any type of location in the region.

5. Evolution of two regional innovation clusters in green hydrogen

In addition to macro-level analyses, our data allow examination of emerging regional patterns within climate-tech innovation networks. As a case study, we analyze green hydrogen, an emerging industry increasingly organized around regional innovation clusters known as "hydrogen hubs" (H_2Hubs) or "hydrogen valleys" [42]. National strategies such as Germany's National Hydrogen Strategy (€7 billion investment [43]) and the US National Clean Hydrogen Strategy and Roadmap ($8 billion investment [44]) highlight the political importance of H_2Hubs in scaling domestic green hydrogen industries.

To explore the structure of emerging H_2Hubs, we focus on the two largest clusters in the EU and the US, located in Berlin and Houston, respectively (based on the number of local hydrogen organizations in our data). Hydrogen-related collaborations are mapped within a 50 km radius around each city center. Despite similar network sizes, the clusters exhibit different structures reflecting their regional contexts. In Berlin, the innovation network is centered around governmental organizations and research institutes (e.g., Fraunhofer Institutes), with a focus on early stage innovation activities such as R&D and demonstrations, supported predominantly through grants (Figure 5a,c). In contrast, the network in Houston is organized around oil and gas firms, with a greater emphasis on commercialization, offtake agreements, and deployments (Figure 5b,c). Financial collaborations in Houston also involve a higher share of equity investments compared to Berlin.

Between the Pre-IRA (01.2020–06.2022) and the Post-IRA (07.2022–12.2024) periods, both networks expanded in size. However, while the share of local partnerships of hydrogen firms (i.e., partnerships with other organizations located in the region) increased in Berlin (from 19.3% to 21.9%), it decreased in Houston (from 16.4% to 14.2%), indicating a densification of regional network in Berlin, while, in Houston, hydrogen firms increasingly seek collaborations outside the region.

These trends suggest that Berlin's hydrogen cluster, initially shaped by strong public-sector leadership, is gradually diversifying in terms of actor centrality with the growing centrality of manufacturers, utilities, and research organizations. Sustaining this evolution may require a transition toward greater private sector investment and reduced reliance on government funding. In Houston, the key uncertainty is whether oil and gas firms will maintain long-term commitment to green hydrogen development, particularly amid shifting political incentives.

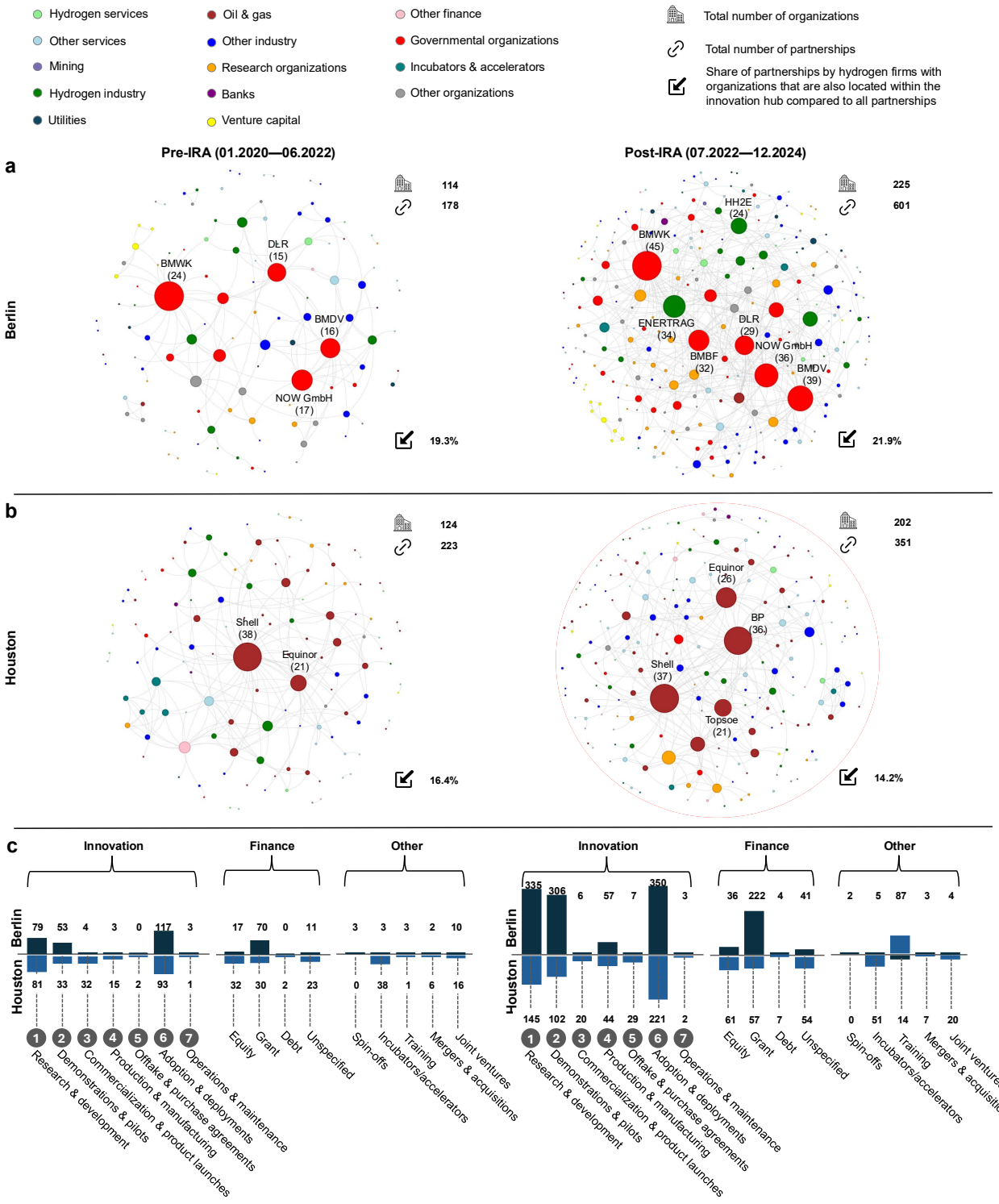


Figure 5: **Comparison of the hydrogen innovation clusters in Berlin and Houston for the periods 01.2020–06.2022 and 07.2022–12.2024.** For comparability, we included all organizations within a 50 km radius around the city centers. **a,b,** Comparison of the network graphs of collaborating organizations. **c,** Comparison of the number of partnerships across different types of collaborations.

6. Discussion

Through our machine learning approach, we have compiled a global dataset comprising 166,459 organizations linked through 442,250 collaborations ($\sim$1.4 million direct partnerships) that contribute to climate-tech innovation. To the best of our knowledge, our dataset enables the first large-scale analysis of innovation networks across different climate technologies, geographies, organizational types, and stages of the innovation process over time. The breadth and granularity of our dataset allow for novel insights into the structural evolution of climate-tech innovation and the role of key actors.

Our findings highlight the important role of governmental organizations in supporting domestic industries in climate-tech. Especially in emerging and scaling technologies that require substantial upfront investment for first-of-a-kind deployments and infrastructure build-up (e.g., direct air capture, geothermal energy, green hydrogen), we find that key governmental organizations, such as the US DOE and the European Commission, act as central actors in global innovation networks and thereby foster partnerships between research, industry, investors, and adopters. Underlying activities reflect the dual role of governmental organizations: both as financiers of innovation activities (e.g., through funding and public procurement) and as active participants, often represented by governmentally owned organizations, such as governmental utilities or accelerator programs. By shaping innovation networks, governmental organizations act as catalysts of industry and market formation and accelerate the development and scaling of climate technologies.

Despite the benefits of governmental involvement facilitating collaborations across organizations, the high degree of network dependency on governmental organizations raises concerns about the resilience of climate-tech innovation systems in the face of shifting political and fiscal priorities. Our data show that 62% of all partnerships either directly involve governmental actors or indirectly depend on their support. Beyond individual projects, sudden and substantial re-

ductions of governmental support could trigger systemic disruptions in climate-tech innovation networks. In this context, the accelerated decline of the German solar industry following the reform of the Renewable Energy Sources Act (EEG) in 2014 serves as a cautionary tale [13]. To ensure long-term stability of innovation networks, policy makers should design strategies for the gradual transition from active ecosystem builders in early-stage industries (e.g., forming partnerships through public procurement and auctions), to facilitators during market adoption (e.g., de-risking investments, incentivizing adoption), and ultimately to a regulatory function in mature markets (e.g., ensuring competition). Establishing clear pathways for policy transition will be essential to support the sustainable growth of climate-tech industries [45].

Our analyses demonstrate substantial structural differences between innovation networks in the US and the EU. Compared to the EU, climate-tech innovation networks in the US are characterized by strong cross-regional connectivity and high degrees of cross-regional specialization. Prior research has shown that cross-regional specialization fosters technological spillovers, shared infrastructure, and the emergence of specialized labor markets, thereby accelerating industrial development [46]. When combined with high levels of cross-regional connectivity, specialization can also enhance trade benefits [47] and improve productivity, employment, and economic growth [48]. Strengthening EU-level coordination–particularly by promoting cross-border partnerships and supporting more diverse regional specialization–could therefore improve the competitiveness of Europe's climate-tech innovation networks and emerging industries.

Our machine learning approach for tracking innovation networks provides substantial advantages compared to existing methodologies in terms of scope, timeliness, and cost-efficiency. To the best of our knowledge, we created the first dataset that systematically captures a broad range of organizations, technologies, and types of innovation collaborations. In contrast, existing datasets used in innovation research are typically either based on small samples (e.g.,

[11, 18]) or confined to a much smaller set of innovation activities. For example, the Crunchbase database [49] primarily focuses investment and funding of private firms. Data by BloombergNEF [29], on the other hand, primarily focus on large-scale deployment finance for mature climate technologies, such as wind and solar, and provide only aggregated estimates on emerging technologies and early-stage innovation activities. Other secondary data sources used in innovation research, such as patent [18, 50] or trade data [21, 22], are also limited to specific stages of the innovation process. In addition, our machine learning approach allows automated data collection in near-real time and with continuous updates, offering scalability and substantially reducing the time lag between innovation activities and their measurement.

Our approach for monitoring innovation is nevertheless subject to limitations. First, while LinkedIn is the largest professional social media platform globally and shows high penetration rates in most countries, coverage varies geographically. As discussed, representativeness is likely lower for Japan, Korea, and China, where LinkedIn usage is either culturally limited or structurally restricted (Supplementary Discussion S1). Despite these gaps, comparisons with external datasets such as i3 (Supplementary Discussion S2) and Crunchbase (Supplementary Discussion S3) demonstrates that our machine learning approach captures a substantial majority of active climate-tech organizations across other countries. Second, despite high incentives for organizations to report collaborations on LinkedIn (e.g., for attracting job applicants, investors, partners, and customers [51, 52, 53]), the degree of information revealed may vary across different types of organizations, as some may be likely to post or be referenced in other posts about innovation collaborations. This is confirmed in our comparison with other datasets where our coverage of organizations from the other datasets increases with organizational size and maturity (Supplementary Table S5,S9,S10; note that our total sample size of climate-tech organizations is much higher than those of other datasets). We find no considerable variations in coverage across technological sectors (Supplementary Table S4). Third, our data may be biased

to organizations that were active during our data collection. As such, we did not capture organizations that exited the market and deleted their LinkedIn profile before the first data collection. Frequent updates in our data retrieval will allow us to eliminate this bias in the future and also help us identify market exits and failures of organizations.

In the future, our machine learning approach can be used to continuously track the progress and evolution of climate-tech innovation networks across various types of organizations, innovation stages, regions, and technologies, even beyond climate-tech. The resulting data can be used to complement other, existing indicators for tracking innovation. Specifically, our data could complement data capturing innovation outcomes, such as patent data for inventions and trade data for late-stage diffusion, as well as other socio-economic indicators capturing employment and economic growth. Linking existing outcome measures to our data on the structure and dynamics of innovation networks would provide fundamentally deeper insights into the factors that make innovation networks successful and help identify policy options to shape innovation networks accordingly.

Methods

6.1. Data

Our global innovation network of climate technologies is based on publicly available information retrieved from the social media platform LinkedIn. LinkedIn is the largest professional social media platform with over 900 million global users worldwide [53, 54]. All data we use is self-reported by organizations through their profile information and posts. As organizations use LinkedIn to attract and retain important stakeholders, such as employees, business partners, and investors, the provided information is generally considered accurate and comprehensive [51, 52, 53].

We retrieved the data through an iterative process, performing three iterations. In the first iteration, we started with an initial set of 13,235 organizations provided by the climate technology organizations database from BloombergNEF [29], which has a global coverage of climate technology organizations. The database includes the organizations' website addresses from which we retrieved corresponding LinkedIn accounts as initial input to our machine learning approach. In subsequent iterations, the LinkedIn accounts of organizations were then identified by analyzing the involvement of new organizations in climate-tech collaborations (see Section "Iterative process").

To retrieve data on organizations, we directly accessed the profiles of organizations through the web. In particular, we retrieved two types of data: (1) metadata of organizations and (2) post data, as follows.

(1) Metadata include: (i) the locations of organizations, (ii) account data that is automatically compiled by LinkedIn, and (iii) organizational attributes that are self-reported by the organization. Locations are provided at the address level (including country, city, postal code, street, and street number). We converted all addresses into geolocations in the form of longitude and latitude coordinates using the Python geopy package [55]. Notably, 36.1% of the

organizations in our datasets have multiple locations, but organizations have to indicate which one of the locations is considered their the headquarter. For 12,842 organizations (7.7% of all organizations), no location was provided. LinkedIn profiles of organizations also indicate the number of employees based on LinkedIn members working at the organization and the number of followers on Linkedin. Self-reported data have the following attributes: the founding year; the website address; a description of the organization; the number of employees (as a range); the industry of the organization; a list of hashtags that are relevant to the organization; and a list of "specialities", which comprises technologies, services, and industries related to the organizations' businesses. Overall, we collected and analyzed the metadata of 166,459 organizations.

(2) Post data refer to all LinkedIn posts by the organization. Post data include the text of the post, the date of the post, all other referenced organizations with LinkedIn accounts, and whether the post is a repost or an original post. Of note, we retrieved all LinkedIn posts of organizations from the first post of the company until the date of the data retrieval. To avoid double counting, we excluded reposts from our analysis. For each organization, we retrieved all historical posts from the date when the organization joined LinkedIn to our retrieval date. To account for different languages, we classified the language of each post using the fasttext package of Python [56] and translated all non-English text into English using the Google Translate API [57]. Overall we collected and analyzed 26 million posts. The data was collected in 2023/24 and spans collaborations from January 2017 to December 2024.

6.2. Network graph

We created a bipartite network [58] of organizations and climate-tech innovation collaborations [58]. We define climate-tech innovation collaborations as individual projects (e.g., demonstration projects, deployments) and other types of interactions (e.g., equity investments, mergers and acquisitions) through which multiple organizations contribute to climate-tech innovation (exemplary posts of climate-tech innovation collaborations are provided in Supple-

mentary Table S17). We retrieved the collaborations from LinkedIn posts of organizations where we analyze whether the posts announce a collaboration between two or more organizations (see Section "Machine learning approach"). Formally, our bipartite network is a graph $G = \{O, C, E\}$, where O and C represent nodes of organizations and collaborations respectively, and where $E = \{(o, c) : o \in O, c \in C\}$ are the links between the two. Both types of nodes, O and C, have further attributes related to organizations (e.g., founding year, organization type, locations) and collaboration projects (e.g., technology, collaboration type, post date for collaborations), respectively. As such, organizations are not directly connected in our graph but only through collaboration projects.

Based on the bipartite graph G, we further compute a transformed network $G' = (V', E')$ where V' are the organizations from above and where E' are edges linking two companies that are involved in the same collaboration. In the main paper, we call these direct edges "partnerships". We use the transformed network G' for all network statistics and all plots in the main paper. To avoid double counting, multiple partnerships between the same organizations and with the same characteristics (i.e., climate technology and type of collaboration) are projected onto a single link for a given period. The degree centrality of a specific organization node is then calculated as the sum of its number of partnerships. For plotting the network and computing network characteristics (e.g., clustering coefficient, degree centrality of nodes), we used the Python package NetworkX [59].

6.3. Machine learning approach

Our network was constructed by analyzing organizations and their social media posts with the open-source large language model (LLM) Deepseek-V3 [60], which represents a Mixture-of-Experts language model consisting of 671B parameters that has outperformed other open-source models and achieved a performance comparable with closed-source models, such as GPT-4o [61] and Claude-3.5-Sonnet [62].

We used an iterative process of two steps (details are described below): *(1) organization analysis* and *(2) post analysis*.

(1) Organization analysis: In this step, we analyzed the organization data from LinkedIn. This data originates from LinkedIn profiles tagged as "Company". As Company profiles on LinkedIn include "Educational", "Government Agencies", and "Non Profit", we refer to underlying entities as *organizations* throughout the paper.

Specifically, we used the profile description, industry tag, and speciality tags self-reported by the organizations to classify the organization type (e.g., manufacturer, venture capital, university) and the sector of the organizations. Instead of using the industry category from LinkedIn, we opted for our own set of categories for two reasons: first, the industry category from LinkedIn does not provide information on the specific sector of organizations. Second, it only provides a single tag, while most organizations can be attributed to multiple organization types (e.g., utilities and project developers; accelerators and venture capital firms; governmental organizations and banks). Our sector categories are based on the STAN industry list by the Organization of Cooperation and Development [63]. Within the energy and climate sectors, we used more granular sub-sector categories (e.g., hydrogen, direct air capture, oil, gas). The full list of categories for organization types and sectors used in our dataset are provided in the Supplementary Tables S22 and S21. To automate the above analysis, we designed two classifiers: (i) an organization type classifier and (ii) a sector classifier, as described in the following.

(i) For the organization type classifier, we leveraged in-context learning with few-shot examples containing manual annotations. Specifically, we constructed a prompt containing a short instruction and manual annotations of exemplary organization profiles with organization type labels (Supplementary Table S24). We designed the organization type classifier for multi-class classification, thus allowing each organization to be mapped to multiple organization types (e.g., an organization can be both a manufacturer and project developer). To ensure replicability, the

temperature was set to 0. We tested the final performance of the classifier on manually annotated LinkedIn accounts, where it achieves an out-of-sample micro F1-score of 0.95 (Supplementary Table S22).

(ii) We developed the sector classifier analogously to the organizations classifier, but with a different prompt using the sector labels and different manual annotations of exemplary organizations (Supplementary Tables S23). Our sector classifier also allowed for multi-class classification (e.g., mapping an organization simultaneously onto both the oil and hydrogen sector). The sector classifier achieved an out-of-sample micro F1-score of 0.93 (Supplementary Table S21).

(2) Post analysis: In this step, we analyzed whether LinkedIn posts of organizations represent collaborations related to climate-tech innovation. For this, we this we split the task in two steps. First, we trained and implemented a relevance classifier which only filters posts that are related to climate technologies. The relevance classifier is based on the language model BERT, which has comparatively few parameters and thus lower computational costs [64, 65]. Second, we used DeepSeek-V3 [60] as the LLM to extract collaborations from the posts and classify them regarding relevant types of collaboration and climate technologies. By pre-filtering relevant posts with a highly efficient language model, we reduce the sample size of posts to be analyzed by the LLM by around 81.5%. Such steps substantially reduce computational costs [66]. The classifiers are as follows:

(i) The relevance classifier for climate technologies is a binary classifier that classifies whether a post is related to climate technologies. To be classified as relevant, a post must discuss a specific climate technology or primarily relate to decarbonizing a sector or process (e.g., decarbonization of cement). To deal with the large volume of input data (around 26 million posts), we trained a supervised classifier based on the language model BERT [64] on a set of 10,000 manually annotated posts (details on the model architecture and training setup are provided in the Supplementary Discussion S5. The climate-tech relevance classifier achieved

an out-of-sample F1-score of 0.97 (Supplementary Table S25).

(ii) The collaboration extraction and classification is based on the Deepseek-V3 model in inference state with a prompt containing the task instruction and few-shot examples for in-context learning (the full prompt is provided in the Supplementary Table S27). To ensure replicability, the temperature was set to 0. The model performs the following three tasks:

1. *Collaboration relevance:* the model classifies whether a post announces a collaboration between two or more organizations (which must be referenced explicitly and tagged with their LinkedIn handle (organization_name)) and extracts the collaborating organizations. By only including posts that publicly tag partnering organizations, we aim to mitigate that posting organizations fake or exaggerate their involvement in innovation collaborations. Furthermore, we only consider collaborations that are contributing to the innovation process as relevant. For example, we did not include joint participation in events such as panels, conferences, or industry fairs. If multiple, independent collaborations are announced, the model extracts them separately.
2. *Technology classification:* the model maps each collaboration onto a list of 27 climate technologies (e.g., solar, hydrogen, and direct air capture; the full list of climate technologies, including a definition and exemplary posts is provided in the Supplementary Table S18).
3. *Collaboration type classification:* the model maps each collaboration onto a list of 17 collaboration types (e.g., R&D collaboration, equity investment, and joint venture; the full list of collaboration types, including a definition and exemplary posts is provided in the Supplementary Table S17).

Both climate technology and collaboration type labels are non-exclusive, allowing collaborations to be mapped onto multiple labels.

For each task, the performance of the LLM was validated ex-post via manual inspection

of a random sample of classified posts. The collaboration relevance classification achieved an out-of-sample F1-score of 0.95; the technology classification achieved an out-of-sample micro F1-score of 0.95; and the collaboration type classification achieved an out-of-sample micro F1-score of 0.96 (detailed performances across individual categories are reported in the Supplementary Table S26).

6.4. Iterative process

Based on the organization analysis and the post analysis of the machine learning approach, we ran three iterations of our data collection process where, in each iteration, the network was extended by adding newly identified organizations and collaborations. To identify new organizations, we extracted the involved organizations from each collaboration. If an organization was not yet included in our database, we added it to our database. For the newly added organizations, we restarted the machine learning approach from above retrieving and analyzing metadata and post data of organizations.

We ran the machine learning approach for three iterations: once with the initial set of organizations from BloombergNEF and once for the second set of newly added climate-tech organizations identified during the organization processing step. In the third iteration, we only retrieved and analyzed the organizational metadata to allow for complete analyses of innovation network participants. Overall, we started with 13,235 organizations from BloombergNEF and found 121,492 new organizations engaging in climate-tech innovation based on 399,318 identified collaborations in climate-tech.

6.5. Validation

To assess the representativeness of the data generated by our machine learning approach, we validated the data against established databases commonly used to study climate-tech innovation (Supplementary Discussions S1–S3). Our validations show that our machine learning

approach is able to capture the vast majority of active climate-tech organizations and partnerships identified in databases. While coverage is likely lower for China, Japan, and Korea due to limited LinkedIn activity, we observe no systematic variation across sectors. Furthermore, we find particularly strong coverage for organizations with more than 10 employees and activities beyond the concept or pre-seed stages. Overall, our data encompass a substantially larger and more diverse set of organizations and partnerships than the databases used for comparison.

References

1. D. Popp, Environmental policy and innovation: a decade of research, National Bureau of Economic Research (2019).
2. IEA, Net zero by 2050, 2021. URL: https://www.iea.org/reports/net-zero-by-2050.
3. IEA, Energy technology perspectives 2020: Special report on clean energy innovation (2020).
4. J. Bistline, G. Blanford, M. Brown, D. Burtraw, M. Domeshek, J. Farbes, A. Fawcett, A. Hamilton, J. Jenkins, R. Jones, et al., Emissions and energy impacts of the Inflation Reduction Act, Science 380 (2023) 1324–1327.
5. European Commission, The Green Deal Industrial Plan, 2024. URL: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal/green-deal-industrial-plan_en.
6. M. P. Hekkert, R. A. A. Suurs, S. O. Negro, S. Kuhlmann, R. E. Smits, Functions of innovation systems: A new approach for analysing technological change, Technological Forecasting and Social Change 74 (2007) 413–432.
7. K. S. Gallagher, A. Grübler, L. Kuhl, G. Nemet, C. Wilson, The energy technology innovation system, Annual Review of Environment and Resources 37 (2012) 137–162.
8. S. Haakonsson, Changing geography of clean tech, Nature Energy 5 (2020) 735–736.
9. C. Lechner, C. Leyronas, The competitive advantage of cluster firms: the priority of regional network position over extra-regional networks–a study of a french high-tech cluster, Entrepreneurship & Regional Development 24 (2012) 457–473.
10. H. Overholm, Collectively created opportunities in emerging ecosystems: the case of solar

service ventures, Technovation 39 (2015) 14–25.

11. C. Doblinger, K. Surana, L. D. Anadon, Governments as partners: The role of alliances in US cleantech startup innovation, Research Policy 48 (2019) 1458–1475.

12. J. Noailly, V. Shestalova, Knowledge spillovers from renewable energy technologies: Lessons from patent citations, Environmental Innovation and Societal Transitions 22 (2017) 1–14.

13. G. F. Nemet, How solar energy became cheap: A model for low-carbon innovation, Routledge, 2019.

14. A. Elia, M. Kamidelivand, F. Rogan, B. Ó. Gallachóir, Impacts of innovation on renewable energy technology cost reductions, Renewable and Sustainable Energy Reviews 138 (2021) 110488.

15. A. Stephan, L. D. Anadon, V. H. Hoffmann, How has external knowledge contributed to lithium-ion batteries for the energy transition?, iScience 24 (2021) 101995.

16. J. Huenteler, J. Ossenbrink, T. Schmidt, V. H. Hoffmann, How a product's design hierarchy shapes the evolution of technological knowledge—evidence from patent-citation networks in wind power, Research Policy 45 (2016) 1195–1217.

17. I. D. Lacasa, M. H. Shubbak, Drifting towards innovation: The co-evolution of patent networks, policy, and institutions in China's solar photovoltaics industry, Energy Research & Social Science 38 (2018) 87–101.

18. K. Surana, C. Doblinger, L. D. Anadon, N. Hultman, Effects of technology complexity on the emergence and evolution of wind industry manufacturing locations along global value chains, Nature Energy 5 (2020) 811–821.

19. A. Goldstein, C. Doblinger, E. Baker, L. D. Anadón, Patenting and business outcomes for cleantech startups funded by the advanced research projects agency-energy, Nature Energy

5 (2020) 803–810.

20. M. Cardenas Rodriguez, I. Haščič, N. Johnstone, J. Silva, A. Ferey, Renewable energy policies and private sector investment: Evidence from financial microdata, Environmental and Resource Economics 62 (2015) 163–188.

21. S. Halleck-Vega, A. Mandel, K. Millock, Accelerating diffusion of climate-friendly technologies: A network perspective, Ecological Economics 152 (2018) 235–245.

22. D. Fadly, F. Fontes, Geographical proximity and renewable energy diffusion: An empirical approach, Energy Policy 129 (2019) 422–435.

23. N. Ameli, S. Kothari, G. Livan, G. Caldarelli, The hidden structure of energy efficiency finance, Available at SSRN 3895862 (2021).

24. R. Gross, R. Hanna, A. Gambhir, P. Heptonstall, J. Speirs, How long does innovation and commercialisation in the energy sectors take? Historical case studies of the timescale from invention to widespread commercialisation in energy supply and end use technology, Energy Policy 123 (2018) 682–699.

25. G. F. Nemet, V. Zipperer, M. Kraus, The valley of death, the technology pork barrel, and public support for large demonstration projects, Energy policy 119 (2018) 154–167.

26. N. Wang, K. Akimoto, G. F. Nemet, What went wrong? Learning from three decades of carbon capture, utilization and sequestration (CCUS) pilot and demonstration projects, Energy Policy 158 (2021) 112546.

27. Intergovernmental Panel on Climate Change, Climate change 2022: mitigation of climate change, 2022. URL: https://www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_FullReport.pdf.

28. M. Toetzke, B. Probst, S. Feuerriegel, Leveraging large language models to monitor climate technology innovation, Environmental Research Letters 18 (2023) 091004.

589 29. BloombergNEF, BloombergNEF, 2023. URL: https://www.bnef.com/.

590 30. IEA, ETP clean energy technology guide, 2025. URL: https:
591 //www.iea.org/data-and-statistics/data-tools/
592 etp-clean-energy-technology-guide.

593 31. ITER, The project: Building ITER, 2025. URL: https://www.iter.org/
594 building-iter.

595 32. Commonwealth Fusion Systems, SPARC: Proving commercial fusion energy is possible,
596 2025. URL: https://cfs.energy/technology/sparc.

597 33. L. D. Anadon, G. Chan, A. G. Harley, K. Matus, S. Moon, S. L. Murthy, W. C. Clark,
598 Making technological innovation work for sustainable development, Proceedings of the
599 National Academy of Sciences 113 (2016) 9682–9690.

600 34. U.S. Department of Energy, The infrastructure investment and jobs act, 2022.
601 URL: https://www.energy.gov/sites/default/files/2021-12/FECM%
602 20Infrastructure%20Factsheet.pdf.

603 35. M. Jayachandran, R. K. Gatla, A. Flah, A. H. Milyani, H. M. Milyani, V. Blazek, L. Prokop,
604 H. Kraiem, Challenges and opportunities in green hydrogen adoption for decarbonizing
605 hard-to-abate industries: A comprehensive review, IEEE Access 12 (2024) 23363–23388.

606 36. F. Huber, On the role and interrelationship of spatial, social and cognitive proximity: Per-
607 sonal knowledge relationships of R&D workers in the Cambridge information technology
608 cluster, Regional Studies 46 (2012) 1169–1182.

609 37. M. Grubb, J.-C. Hourcade, K. Neuhoff, Planetary economics, Routledge London, 2014.

610 38. R. Mudambi, Location, control and innovation in knowledge-intensive industries, Journal
611 of Economic Geography 8 (2008) 699–725.

612 39. M. Mazzucato, Mission-oriented innovation policies: challenges and opportunities, Indus-

trial and Corporate Change 27 (2018) 803–815.

40. S. Borrás, C. Edquist, The choice of innovation policy instruments, Technological Forecasting and Social Change)) 80 (2013) 1513–1522.

41. K. Flanagan, E. Uyarra, M. Laranja, Reconceptualising the 'policy mix'for innovation, Research Policy 40 (2011) 702–713.

42. IRENA, Global hydrogen trade to meet the 1.5°c climate goal, 2022. URL: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2022/Jul/IRENA_Global_hydrogen_trade_part_1_2022_.pdf.

43. BMWK, The national hydrogen strategy, 2020. URL: https://www.bmwk.de/Redaktion/EN/Publikationen/Energie/the-national-hydrogen-strategy.pdf?__blob=publicationFile.

44. U.S. Department of Energy, U.S. National Cöean Hydrogen Strategy and Roadmap, 2023. URL: https://www.hydrogen.energy.gov/docs/hydrogenprogramlibraries/pdfs/us-national-clean-hydrogen-strategy-roadmap.pdf?sfvrsn=c425b44f_5.

45. J. Meckling, T. Sterner, G. Wagner, Policy sequencing toward decarbonization, Nature Energy 2 (2017) 918–922.

46. G. Duranton, A. J. Venables, Place-based policies for development, National Bureau of Economic Research (2018).

47. T. Kemeny, M. Storper, Is specialization good for regional economic development?, Regional Studies 49 (2015) 1003–1018.

48. H. L. F. de Groot, J. Poot, M. J. Smit, Agglomeration externalities, innovation and regional growth: theoretical perspectives and meta-analysis, in: Handbook of regional growth and

development theories, Edward Elgar Publishing, 2009.

49. Crunchbase, Crunchbase data, 2025. URL: https://about.crunchbase.com/.

50. B. Probst, S. Touboul, M. Glachant, A. Dechezleprêtre, Global trends in the invention and diffusion of climate change mitigation technologies., Nature Energy (2021).

51. S. Pisano, L. Lepore, R. Lamboglia, Corporate disclosure of human capital via LinkedIn and ownership structure: An empirical analysis of European companies, Journal of Intellectual Capital 18 (2017) 102–127.

52. J. Park, I. B. Wood, E. Jing, A. Nematzadeh, S. Ghosh, M. D. Conover, Y.-Y. Ahn, Global labor flow network reveals the hierarchical organization and dynamics of geo-industrial clusters, Nature Communications 10 (2019) 3449.

53. K. Rajkumar, G. Saint-Jacques, I. Bojinov, E. Brynjolfsson, S. Aral, A causal test of the strength of weak ties, Science 377 (2022) 1304–1310.

54. World Population Review, LinkedIn users by country 2024, 2024. URL: https://worldpopulationreview.com/.

55. GeoPy, GeoPy documentation, 2023. URL: https://geopy.readthedocs.io/en/stable/index.html.

56. fasttext, fasttext 0.9.2, 2023. URL: https://pypi.org/project/fasttext/.

57. Google Cloud, Cloud Translation API, 2023. URL: https://cloud.google.com/translate/docs/reference/rest/.

58. D. V. Filho, D. R. J. O'Neale, The role of bipartite structure in R&D collaboration networks, Journal of Complex Networks 8 (2020) cnaa016.

59. A. Hagberg, P. Swart, D. S Chult, Exploring network structure, dynamics, and function using NetworkX, 2008.

60. A. Liu, B. Feng, B. Xue, B. Wang, B. Wu, C. Lu, C. Zhao, C. Deng, C. Zhang, C. Ruan, et al., DeepSeek-v3 technical report, arXiv preprint arXiv:2412.19437 (2024).

61. OpenAI, API platform, 2025. URL: https://openai.com/product.

62. ANTHROPIC, Claude 3.5 Sonnet, 2025. URL: https://www.anthropic.com/news/claude-3-5-sonnet.

63. OECD, Stan industry list, 2023. URL: https://web-archive.oecd.org/2012-06-15/127386-40729523.pdf.

64. J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, Bert: Pre-training of deep bidirectional transformers for language understanding, arXiv preprint arXiv:1810.04805 (2018).

65. D. Kim, C. Park, S. Kim, W. Lee, W. Song, Y. Kim, H. Kim, Y. Kim, H. Lee, J. Kim, et al., SOLAR 10.7B: Scaling large language models with simple yet effective depth up-scaling, arXiv preprint arXiv:2312.15166 (2023).

66. M. A. K. Raiaan, M. S. H. Mukta, K. Fatema, N. M. Fahad, S. Sakib, M. M. J. Mim, J. Ahmad, M. E. Ali, S. Azam, A review on large language models: Architectures, applications, taxonomies, open issues and challenges, IEEE Access (2024).

67. LinkedIn, Statistics, 2024. URL: https://news.linkedin.com/about-us#Statistics.

68. LinkedIn, China: Sunset of localized version of linkedin and launch of new injobs app later this year, 2021. URL: https://www.linkedin.com/blog/member/product/china-sunset-of-localized-version-of-linkedin-and-launch-of-new-injobs-

69. World Bank, World Bank Open Data, 2024. URL: https://data.worldbank.org/.

70. Cleantech Group, i3, 2023. URL: https://i3connect.com/.

71. J.-M. Dalle, M. Den Besten, C. Menon, Using crunchbase for economic and managerial

research (2017).

72. statsmodels, statsmodels 0.14.4, 2025. URL: https://www.statsmodels.org/stable/index.html.

73. N. Webersinke, M. Kraus, J. A. Bingler, M. Leippold, ClimateBERT: A pretrained language model for climate-related text, arXiv preprint arXiv:2110.12010 (2021).

74. M. Toetzke, A. Stünzi, F. Egli, Consistent and replicable estimation of bilateral climate finance, Nature Climate Change 12 (2022) 897–900.

75. A. J. Sietsma, J. D. Ford, J. C. Minx, The next generation of machine learning for tracking adaptation texts, Nature Climate Change 14 (2024) 31–39.

76. V. Sanh, L. Debut, J. Chaumond, T. Wolf, DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter, arXiv preprint arXiv:1910.01108 (2019).

Data availability

All datasets to train and validate the machine learning classifiers are publicly available via via `https://github.com/MalteToetzke/Code_Repo_2025-06.git`. The data to conduct the analyses will be made publicly available upon acceptance.

Code availability

The code used for the analyses is publicly available via `https://github.com/MalteToetzke/Code_Repo_2025-06.git`. All analyses were conducted using Python 3.13.

Acknowledgements

The authors thank Devjyoti Chakrabarti, Felipe Andres Navarro Martinze, Francesco Re, and Zsofia Rozenberszki for research assistance and Johannes Brehm, Florian Egli, Alejandro Nuñez-Jimenez, Tobias Schimanski, Anna Stünzi, and Hergen Wolf for helpful comments on earlier drafts of the paper. M.T. acknowledges funding from the Swiss National Science Foundation (SNSF) as part of grant 186932 as well as from the Swiss Federal Office of Energy's "SWEET" program as part of the PATHFNDR consortium during his Ph.D. studies, and from the TU Munich Global Postdoc Fellowship and the Friedrich Schiedel Fellowship during his postdoc.

Author contributions

M.T. conceptualized the idea, developed the methods, and performed the data analysis. All authors contributed to the interpretation of the results and the writing of the paper.

Competing interests

The authors declare no competing interests.

Supplementary Information for

Analyzing the dynamics of innovation networks in climate technologies

Malte Toetzke[a,b,*], Benedict Probst[b,c,f], Stefan Feuerriegel[d,e], Laura Diaz Anadón[f,g], Volker Hoffmann[c]

[a]TU Munich, Munich, Germany
[b]bMax Planck Institute for Innovation and Competition, Munich, Germany
[c]ETH Zurich, Zurich, Switzerland
[d]LMU Munich, Munich, Germany
[e]Munich Center for Machine Learning, Munich, Germany
[f]University of Cambridge, Cambridge, United Kingdom
[g]Harvard University, Cambridge, United States

[*]Correspondence to: malte.toetzke@tum.de

This PDF file includes:

Supplementary Discussions S1–S5

Supplementary Figures S1–S36

Supplementary Tables S1–S30

Supplementary Discussions

S1: Discussion of data coverage

The scope of our analysis and the robustness of our conclusions depend on the completeness of the underlying data. As with all empirical studies based on digital trace data, incomplete coverage introduces the potential for systematic biases. In our case, the completeness of our data is influenced by two primary factors: (1) the representativeness of LinkedIn as our primary data source—specifically, the extent to which relevant organizations maintain an active presence on the platform; and (2) the performance of our machine learning pipeline in identifying relevant organizations and extracting innovation collaborations from their publicly available posts. Overall, these factors can introduce biases related to organization characteristics, such as countries, organization type, and size, as follows.

(1) Representativeness of LinkedIn as a data source:

Our analyses rely on the assumption that LinkedIn provides sufficiently broad and diverse representation of climate-relevant organizations. With over 900 million registered users globally, LinkedIn is considered the largest professional social media platform worldwide [53, 54]. Over 67 million of these users are accounts that represent organizations (e.g., companies, universities, public-sector bodies) [67]. Unlike general-purpose platforms such as Twitter or Facebook, LinkedIn incentivizes organizations to disclose information on business activities to attract key stakeholders including employees, partners, and investors [51, 52, 53]. These incentives are particularly strong for organizations engaged in innovation and growth sectors.

However, the LinkedIn representation of organizations may vary across geographies and organization sizes. National-level bias stems in part from varying platform penetration rates. Countries with the largest absolute numbers of users include the United States (200 million), India (99 million), and China (60 million). Since 2021, LinkedIn has operated a separate platform in China (InJobs) which does not support social features [68]. As a result, Chinese or-

ganizations with a domestic focus are likely underrepresented in our dataset, while firms with international presence are more readily captured. This presumption is confirmed in the Supplementary Figure S1, which shows that more than half of Chinese organizations in our data have more than 1,000 employees compared to only 16.6% globally.

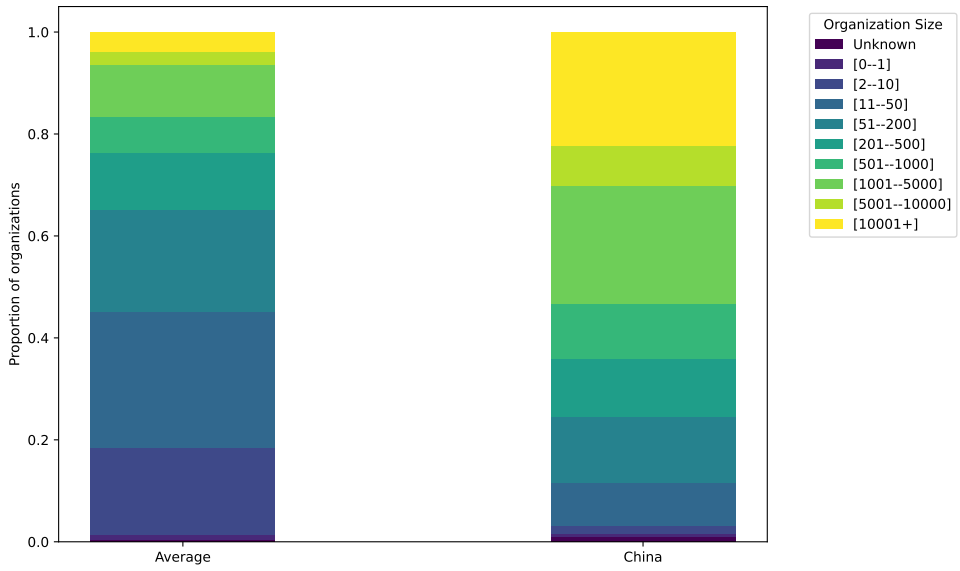


Fig. S1: Distribution of organizations across employee sizes compared between the full sample and China. Companies are attributed to countries based on the respective headquarter location.

To evaluate representativeness across other countries, we examine LinkedIn user rates normalized by population and compare them with GDP per capita (Supplementary Figure S2). We find a moderate positive correlation between LinkedIn penetration and national income levels, supporting the idea that individuals with higher income are more likely to engage in professional networking [53]. We assume that, for countries aligning with this pattern, LinkedIn provides similar incentives for organizations to join the network and disclose information to attract talent and partners. Countries with disproportionately high user rates relative to GDP include the United Arab Emirates, Brazil, Canada, and Singapore, suggesting an above average importance of LinkedIn in these countries. By contrast, user rates are markedly lower in countries such as Japan and South Korea, indicating that LinkedIn plays a less important role in these countries.

Our validation against data from the i3 database (Supplementary Discussion S2) further shows that around half of the companies that could not be matched with our data have no LinkedIn accounts or are inactive on LinkedIn. Only one of the 54 manually assessed companies counts more than 50 employees. This suggests that companies without LinkedIn accounts or activity likely represent small organizations.

Table S1: Top 30 countries by total number of LinkedIn users based on data from 2023 [54].

Country	**LinkedIn users (in 1'000s)**
United States	200,000
India	99,000
China	60,000
Brazil	59,000
United Kingdom	35,000
France	26,000
Indonesia	23,000
Canada	21,000
Mexico	19,000
Italy	17,000
Spain	17,000
Germany	15,000
Australia	14,000
Philippines	13,000
Turkey	13,000
Colombia	12,000
South Africa	11,000
Argentina	11,000
Netherlands	10,000
Pakistan	9,300
Egypt	7,900
Peru	7,700
Nigeria	7,500
Saudi Arabia	7,300
Malaysia	7,000
Chile	6,900
United Arab Emirates	6,600
Bangladesh	5,900
Poland	5,500
Vietnam	5,200

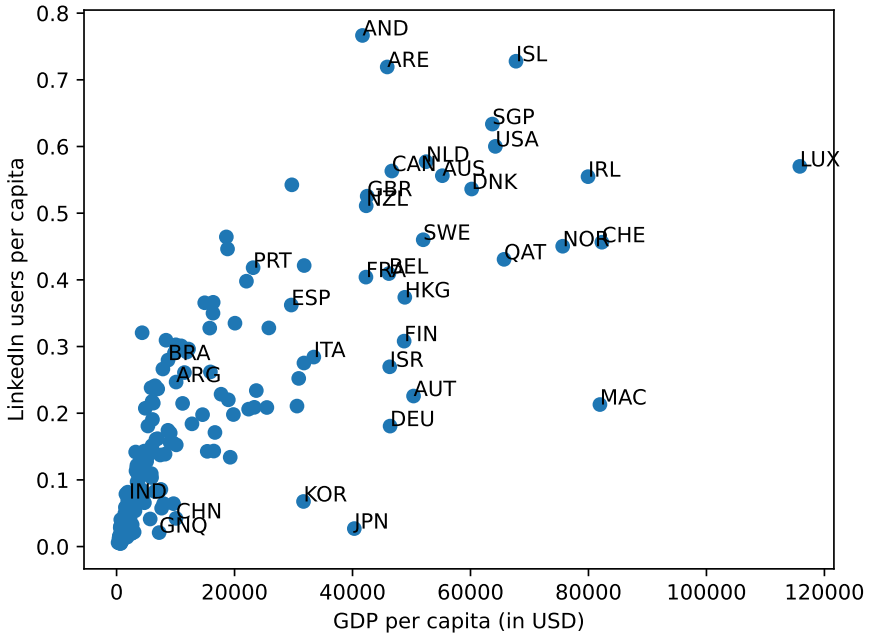


Fig. S2: Comparison between number of LinkedIn users per capita and gross domestic product (GDP) per capita across countries based on data from [54, 69].

(2) Quality of our machine learning approach in identifying relevant organizations and extracting innovation collaborations from their posts:

Our machine learning approach identifies climate-tech organizations through references to joint innovation collaborations mentioned by partnering organizations. Consequently, whether a climate-tech organization is captured in our network depends on two conditions: first, that the organization has engaged in at least one collaboration with an organization already present in our network; and second, that this collaboration was disclosed via LinkedIn posts. This reliance on collaborative disclosure introduces potential sources of bias. Organizations that are smaller, less active in externally visible collaborations, or engaged in partnerships deemed too minor for public announcements by other organizations may be underrepresented. Additionally, regional biases could arise where the density of LinkedIn activity is lower, particularly in regions already identified as having weaker platform penetration.

Validation: To validate our analyses, we provide empirical support for the quality and coverage of our machine learning approach. To this end, we validate our data against two databases, i3 [70] and Crunchbase [49], which are commonly used in innovation research. While the i3 database focuses on companies and partnerships related to sustainability, Crunchbase focuses primarily on startups and funding relationships across different sectors. When it comes to climate-tech specifically, both databases show substantially lower coverage compared to our data. Yet, analyzing how well climate-tech organizations and partnerships from i3 and Crunchbase are captured by our data helps to assess potential biases in our data representation, across different organizational characteristics, such as countries, size, and maturity.

Validation against the i3 database shows that 86.3% of active climate-tech organizations were captured by our approach, and that 79.0% of formally recorded partnerships were also detected. Importantly, the i3 database aggregates information from multiple independent sources and curates organizational and partnership data, minimizing self-reporting bias. This strength-

ens the credibility of the observed high coverage rates in our dataset. Further analysis reveals that matching rates are relatively consistent across sectors, with slightly lower matching in the wind sector (82%) and highest coverage in nuclear fission (96%) (Supplementary Table S4). Similarly, across stages of organizational development, companies at the "Concept" stage exhibit a lower matching rate (76%), whereas organizations with shipping products, pilots, or commercially available products show higher rates, close to or exceeding 85% (Supplementary Table S5). In terms of ownership, matching is marginally higher for public companies (95%) compared to private companies (86%) (Supplementary Table S3). Of note, our manual assessment of 100 randomly drawn companies from the i3 database, only 13 are companies that could be matched (i.e., they have LinkedIn accounts and are active on LinkedIn). From these 13 companies, none was reported in the i3 database to have any employees.

Validation against the Crunchbase database (Supplementary Section 6.5) reveals a somewhat lower organizational matching rate of 69.2%. However, this difference must be interpreted cautiously. Crunchbase is a self-reported platform where companies voluntarily create profiles to enhance their visibility, particularly to investors. As such, Crunchbase covers a broader range of firms, including many that may have, so far, limited or no active engagement in innovation collaborations. Importantly, our analysis of the Crunchbase sample reveals that the matching rate increases systematically with company size and funding maturity. Firms with more than 10 employees are matched at above-average rates, suggesting that larger organizations are more likely to engage in, and publicly disclose, collaborative innovation activities. Similarly, companies that have progressed beyond early-stage funding rounds (e.g., Series A or later, or secured non-equity funding such as debt or private equity) also exhibit higher matching rates, reflecting their greater market engagement and visibility. By contrast, early-stage startups, particularly those in pre-seed or seed phases, are less frequently captured in our LinkedIn-derived network, consistent with their limited embeddedness in formal innovation ecosystems.

Together, these validation exercises suggest that our machine learning approach is highly effective in identifying organizations engaging in climate-tech innovation collaborations. Nonetheless, we acknowledge a potential underrepresentation of very early-stage companies, micro-enterprises, and organizations operating in low-LinkedIn-penetration regions (e.g., China, Japan, Korea). Overall, our dataset still captures a substantially larger number of climate-tech organizations than either the i3 or Crunchbase databases, reflecting the broader scope of our data collection approach. In total, our network includes 70,181 active organizations with a primary focus on climate-tech, providing a uniquely large and detailed view of the global climate innovation landscape.

Finally, as our iterative machine learning process for extracting innovation collaborations and identifying new organizations runs continuously, the completeness of the dataset is expected to increase over time. Ongoing enrichment of the network structure will further improve coverage, particularly for newly active firms and collaborations that emerge beyond the current observation window.

S2: Validation via i3

To assess the completeness of our innovation network dataset, we validated our results against the i3 database curated by the CleanTech Group [70], which is considered one of the most comprehensive datasets covering companies and collaborations in the global cleantech sector [11]. We evaluated the completeness of our dataset along two dimensions: (1) coverage of organizations and (2) coverage of partnerships.

(1) Completeness of organizational coverage:

To validate organizational coverage, we compared the companies listed in the i3 database with those identified in our LinkedIn-based network data. As of August 2024, the i3 database includes 39,144 companies. To achieve a sample of companies engaged in climate-tech in accordance with our focus, we filtered the variable *Sector Tag* for the following categories: 'solar', 'energy storage', 'wind', 'nuclear fusion', 'hydrogen', 'biomass & waste-to-energy', 'nuclear fission', 'electric vehicle (ev) charging','rail', 'geothermal', 'hydro & marine', and 'fuel cells'. This results in a subsample of 6,964 climate-tech companies. Furthermore, by selecting only active firms, we obtained a sample of 5,104 active climate-tech companies. Of note, this sample is considerably lower compared to our sample of active organizations with a primary focus on climate-techs (70,181 organizations). Nevertheless, we now analyze how well climate-tech companies from the i3 database can be matched with our data across different organizational characteristics (e.g., country, size, maturity), which helps identify potential biases in the representation of companies.

We matched organizations between the two datasets using a two-step procedure: first, by matching web domains, and second, by matching cleaned company names and countries (removing legal suffixes such as "Ltd" or "Inc."). Using this approach, we matched 4,404 out of 5,104 firms, corresponding to a match rate of 86.3%.

To assess the reasons why companies from the i3 could not be matched with organiza-

tions from our data, we manually evaluated a random sample of 100 companies from the i3 database that were not matched. As shown in the Supplementary Figure S3, only 13 of these companies could have been captured by our machine learning approach. All other companies either changed their names or lacked Linkedin activity. Of note, none of the 13 companies that could have been captured by our machine learning approach has employees indicated in the i3 database (Supplementary Table S2).

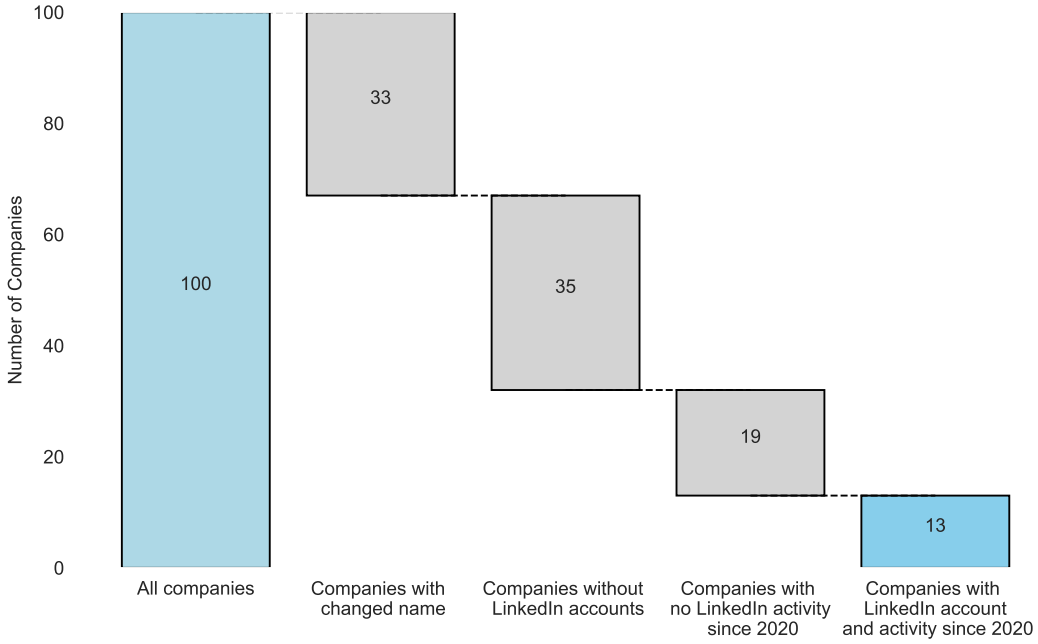


Fig. S3: Breakdown of 100 randomly-sampled companies of the i3 database that could not be matched to organizations from our data.

Table S2: Number of employees indicated in the i3 database for the companies from Supplementary Figure S3. Breakdown by companies (1) without LinkedIn account, (2) with no LinkedIn activity since 2020, and (3) with LinkedIn account and activity since 2020.

Employee Count	**(1) Companies without LinkedIn account**	**(2) with no LinkedIn activity since 2020**	**(3) Companies with LinkedIn account and activity since 2020**
0	25	10	13
1–10	8	6	0
11–50	2	2	0
$>$ 50 | 0 | 1 | 0 |

In the following, we analyze how the share of companies from the i3 database that could be matched with organizations in our data distributes across various organizational characteristics.

Matching by organizational characteristics:

- **Status (public vs. private):** Public companies exhibit a slightly higher matching rate (95%) compared to private companies (86%) (Supplementary Table S3). This is consistent with expectations, given that public companies are often larger, engaging in a

multitude of partnerships, and maintaining a strong digital presence.

- **Sector:** Matching rates are relatively consistent across sectors (Supplementary Table S4), with nuclear fission companies showing the highest matching rate (96%), and wind sector companies the lowest (82%).

- **Development stage:** Companies in early development stages (*Concept*) show a lower matching rate (76%), whereas companies at more advanced stages (i.e., Product Development (86%), Shipping Product/Pilot (85%), and Wide Commercial Availability (88%)) match at rates comparable to the overall average (Supplementary Table S5).

- **Countries:** Matching rates vary modestly across countries (Supplementary Table S6). Most major countries exceed 80% matching rates, with notable outliers including Lithuania (64%) and Japan (74%). Surprisingly, Chinese companies have a relatively high match rate (88%), which likely reflects lower domestic coverage in the i3 database rather than full representation in our network data.

Table S3: Matching rate of climate-tech companies from the i3 database with our dataset comparing public and private organizations (indicated by the *Status* variable in i3).

Status	**Share of matched companies**	**Number of companies in the i3 database**
Private	0.86	4,724
Public	0.95	380

Table S4: Matching rate of climate-tech companies from the i3 database with our dataset across sectors (indicated by the *Sector Tag* variable in i3).

Sector Tag	**Share of matched companies**	**Number of companies in the i3 database**
solar	0.85	1,736
energy storage	0.89	802
wind	0.82	634
biomass & waste-to-energy	0.83	471
electric vehicle (EV) charging	0.90	450
hydrogen	0.90	434
hydro & marine	0.87	217
fuel cells	0.86	111
geothermal	0.85	78
nuclear fission	0.96	72
nuclear fusion	0.91	64
rail	0.89	35

Table S5: Matching rate of climate-tech companies from the i3 database with our organizations data across development stages (indicated by the *Development Stage* variable in i3).

Development Stage	**Share of matched companies**	**Number of companies in the i3 database**
Wide Commercial Availability	0.88	2,264
Shipping Product / Pilot	0.85	1,197
Product Development	0.86	960
Concept	0.76	191

Table S6: Matching rate of climate-tech companies from the i3 database with our organizations data across countries. Due to space, we exclude countries with fewer than two companies.

Country	Share of matched companies	Number of companies in the i3 database
United States	0.87	1,646
United Kingdom	0.90	441
China	0.88	329
Germany	0.84	299
Canada	0.90	260
France	0.84	230
India	0.95	155
Netherlands	0.83	151
Australia	0.93	137
Spain	0.88	121
Switzerland	0.80	113
Norway	0.90	101
Sweden	0.83	94
Italy	0.73	78
Israel	0.76	74
Denmark	0.75	60
South Africa	0.81	54
Finland	0.77	53
Nigeria	0.82	49
Belgium	0.85	48
Austria	0.84	45
Japan	0.74	42
Ireland	0.85	39
Singapore	0.92	37
Korea Republic	0.80	30
Brazil	0.96	28
Turkey	0.81	27
Portugal	0.77	22
Poland	0.86	21
Taiwan	0.95	19
Estonia	0.89	18
New Zealand	0.80	15
Thailand	0.87	15
Indonesia	0.79	14
Hong Kong	1.00	13
Kenya	0.92	13
Greece	0.83	12
Lithuania	0.64	11
Russia	0.91	11
Mexico	0.89	9
Cambodia	0.88	8
Vietnam	0.86	7
Bulgaria	0.71	7
Malaysia	1.00	7
Pakistan	1.00	7
United Arab Emirates	0.86	7
Slovakia	0.86	7
Uganda	1.00	6
Luxembourg	1.00	6
Chile	0.80	5
Ukraine	0.60	5
Morocco	0.80	5
Philippines	1.00	4
Romania	1.00	4
Saudi Arabia	1.00	4
Argentina	0.50	4
Ghana	1.00	4
Malawi	0.50	4
Czech Republic	0.50	4
Latvia	1.00	4
Costa Rica	0.67	3
Iceland	1.00	3
Cyprus	1.00	3
Hungary	0.67	3
Rwanda	1.00	3
Kazakhstan	1.00	2
Zambia	1.00	2
Jordan	1.00	2
Mauritius	0.50	2
Slovenia	1.00	2
Egypt	1.00	2
Tanzania	1.00	2

Table S7: Overview of company relationships from the i3 database matched with partnerships in our network, by relationship type. We included relationships between 2020 and 2024 and companies from the industries "energy & power" and "transportation & logistics".

Relationship Type	Share of matched relationships	Number of relationships from i3 (2020–2024)
Technology Partner	77%	131
Development Partner	85%	112
Project Development	82%	101
Joint Venture	74%	35
Customer	87%	30
Channel Partner	57%	21
Licensee	60%	10
Incubation/Acceleration	50%	2

(2) Completeness of partnerships:

To assess the completeness of partnerships in our network, we validated against the "relationships" recorded in the i3 database for the period between 2020 and 2024. To align with our climate-tech focus, we restricted the sample to relationships involving companies categorized under the *Industry Groups* "Energy & Power" and "Transportation & Logistics", resulting in 443 company relationships.

We manually validated if these relationships match with partnerships in our network data. Of the 443 relationships, 350 (79.0%) were matched with partnerships identified in our dataset. Among the unmatched relationships, 16 involved organizations that were not present in our organizational database, suggesting that the absence is partly attributable to missing organizational nodes rather than missing edges. The distributions in the share of matched relationships between different types of relationships and countries are reported in the Supplementary Tables S7 and S8.

Table S8: Overview of company relationships from the i3 database matched with partnerships in our network, by country. We included relationships between 2020 and 2024 and companies from the industries ”energy & power” and ”transportation & logistics”.

Country	Share of matched relationships	Number of relationships from i3 (2020–2024)
United States	77%	333
Germany	86%	102
United Kingdom	81%	91
France	86%	56
Japan	76%	45
China	62%	39
Canada	79%	29
Sweden	88%	24
Norway	82%	22
Netherlands	69%	16
Australia	75%	16
Denmark	100%	13
Korea Republic	83%	12
Israel	90%	10
Italy	90%	10
India	100%	7
Switzerland	71%	7
Spain	86%	7
Austria	60%	5
Taiwan	100%	5
Greece	67%	3
Estonia	67%	3
Ireland	100%	3
Belgium	100%	2
Singapore	50%	2
Portugal	100%	2
Finland	0%	2
Hong Kong	0%	2
Latvia	50%	2
Vietnam	100%	2
New Zealand	100%	1
Slovakia	0%	1
Malaysia	100%	1
Egypt	100%	1
Lithuania	100%	1
Kenya	0%	1
Indonesia	100%	1

S3: Validation via Crunchbase

The Crunchbase database [49] primarily covers companies' investment and funding activities. It is populated largely through self-reporting by users, including investees and investors, who create organizational profiles to enhance visibility. Due to its extensive coverage of startups and growth-stage firms, Crunchbase is widely used in innovation research to study investment dynamics and emerging technology sectors [71].

To validate the coverage of organizations from our network data, we constructed a filtered subsample of climate-tech companies from Crunchbase. For this, we filtered the following subsample to ensure that we capture relevant companies. First, to ensure relevance for climate-tech, we filtered companies that have a climate-tech-related category in the *category_list* column. Climate-tech-related categories include the following: 'CleanTech', 'Clean Energy', 'Carbon Capture', 'Battery', 'Biofuel', 'Biomass', 'Electric Vehicle', 'Fuel Cell', 'Geothermal Energy', 'Renewable Energy', 'Solar', and 'Wind Energy'. This filtering resulted in a subsample of 7,937 climate-tech companies. Second, to ensure organizational activity during our study period, we selected only companies with recorded funding activities between 2020 and 2024, based on the variable *last_funding_on*. Funding activities range from *pre_seed*, to *ipo*, to *post_ipo_debt* (see all funding categories in the Supplementary Table S10). After filtering, 5,090 active, climate-tech companies remained. Finally, we filtered for companies that have a website (*domain*) or LinkedIn URL (*linkedin_url*) to ensure we can match the companies with organizations in our network database, resulting in a final dataset of 4,310 companies.

Matching was conducted in three sequential steps. In the first step, we matched companies using the LinkedIn URL. Since not all LinkedIn URLs use consistent formats (some employ company handles, others numerical IDs), this step did not capture all possible matches. In the second step, we matched companies using website domain names. In the third step, we matched remaining companies via the Crunchbase URL field (*crunchbaseUrl*) which is partly available

in our organizational database.

Using this procedure, we matched 2,983 out of the 4,310 active climate-tech companies in Crunchbase, corresponding to a matching rate of 69.2%. As shown in the following, the share of matched companies increases with company size and investment maturity. As such, it is above the average matching rate for companies with more than 10 employees and for companies that received a *series a* investment or non-equity funding, such as debt, private equity, or secondary market. For countries, we find above or near average matching rates for most countries. Exceptions with lower matching rates but more than 10 companies on Crunchbase are China (42%), Turkey (50%), Japan (58%), and Korea (50%). These findings are consistent with observations from our broader data coverage discussion (Section S1), where LinkedIn penetration rates were identified as lower in these countries.

Overall, the validation against Crunchbase reinforces the conclusion that our LinkedIn-derived organizational data offers strong coverage of active, growth-oriented firms in the climate-tech sector, particularly among medium-sized and large enterprises. The representativeness appears to be lower for very early-stage startups with less than 10 employees and for companies based in regions with lower LinkedIn engagement (e.g., China, Japan, Korea; see Supplementary Discussion S1. These limitations should be considered when interpreting analyses related to firm size distribution and regional innovation activity.

Validation across company size: The share of companies from Crunchbase that we could match with organizations in our network data strongly correlates with company size (Supplementary Table S9). While the matching rate is below the average for small companies with 10 or fewer employees (50%), it is above average for larger companies and increases with size from 73% for companies between 11 and 50 employees to 92% for companies with more than 5,000 employees. This shows that, with increasing company size, the likeliness of our machine learning approach to capture climate-tech companies increases.

Table S9: Matching rate of climate-tech companies from Crunchbase with our organizations data across company sizes from Crunchbase.

Employee Count	Share of matched companies	Number of companies in Crunchbase
1–10	0.50	1,383
11–50	0.73	1,641
51–100	0.82	412
101–250	0.87	357
251–500	0.85	159
501–1000	0.88	104
1001–5000	0.86	122
5001–10000	0.92	39
10000+	0.92	73
unknown	0.40	20

Validation across funding stages: Similar to company sizes, we see a strong correlation between the matching rate and the maturity of investment types (Supplementary Table S10). While the matching rate is below average for companies that received early-stage funding such as pre-seed, crowdfunding, and seed, we see that, for firms with more mature investments (e.g., series A–H, debt financing, private equity, post-IPO financing), matching rates are above average, showing that the degree to which our machine learning approach captures climate-tech companies increases with increasing investment maturity.

Table S10: Matching rate of climate-tech companies from Crunchbase with our organizations data across the last investment type of companies reported in Crunchbase.

Investment Type	Share of matched companies	Number of companies in Crunchbase
pre_seed	0.37	361
seed	0.59	814
angel	0.42	33
grant	0.68	670
convertible_note	0.71	72
equity_crowdfunding	0.58	69
product_crowdfunding	0.33	6
series_a	0.80	404
series_b	0.86	185
series_c	0.84	62
series_d	0.80	25
series_e	0.82	11
series_f	1.00	1
series_g	1.00	1
series_h	1.00	1
series_unknown	0.76	492
corporate_round	0.75	72
private_equity	0.76	122
secondary_market	0.88	17
debt_financing	0.82	363
non_equity_assistance	0.61	114
initial_coin_offering	1.00	2
post_ipo_equity	0.76	184
post_ipo_debt	0.91	170
post_ipo_secondary	0.75	8
undisclosed	0.68	50

Validation across countries: For countries with more than 20 climate-tech companies on Crunchbase, we find a below-average representation of companies in China (42%), Turkey (50%), Japan (58%), and Korea (50%, Supplementary Table S11). Companies from the US (87%), Canada (90%), Australia (93%), Israel (76%), United Kingdom (90%), and Europe appear to be well represented. Furthermore, in South East Asia, companies from India (71%), the Philippines (100%), and Singapore (69%) are well represented (in contrast to China, Japan, and Korea). In Africa, South Africa (75%), Egypt (71%), Kenya (73%), and Tunisia (75%) are among well-represented countries, while Nigeria (59%) and Zimbabwe have lower representation (50%). For South and Central America, the representativeness varies. While companies from Mexico (42%) and Argentina (50%) are represented below average, companies from Brazil (70%) and Chile (75%) are represented above average.

Table S11: Matching rate of climate-tech companies from Crunchbase with our organizations data across countries. For reasons of space, we exclude countries with fewer than two companies.

Country	Share of matched companies	Number of companies in Crunchbase
USA	0.65	1524
GBR	0.74	369
CAN	0.75	299
IND	0.71	241
FRA	0.81	168
DEU	0.84	167
AUS	0.77	125
NLD	0.77	107
CHE	0.67	91
CHN	0.42	85
ESP	0.83	83
SWE	0.77	77
NOR	0.84	67
ITA	0.69	62
ISR	0.77	56
SGP	0.69	51
BRA	0.70	44
FIN	0.65	43
NGA	0.59	41
DNK	0.89	37
IRL	0.88	34
KEN	0.73	30
TUR	0.50	26
JPN	0.58	26
KOR	0.50	26
EST	0.79	24
BEL	0.71	21
ARE	0.58	19
POL	0.61	18
HKG	0.50	18
PRT	0.75	16
ZAF	0.75	16
AUT	0.80	15
IDN	0.53	15
NZL	0.50	14
MEX	0.42	12
CHL	0.75	12
HUN	0.17	12
ARG	0.50	10
LTU	0.60	10
COL	0.33	9
VNM	0.67	9
ISL	0.75	8
BGR	0.50	8
PHL	0.71	7
LUX	0.71	7
EGY	0.71	7
MYS	0.33	6
HRV	0.17	6
TWN	0.67	6
SAU	0.50	6
LVA	0.40	5
ROM	0.40	5
GRC	0.80	5
PAK	0.25	4
SVK	1.00	4
TUN	0.75	4
ZWE	0.50	4
GHA	0.75	4
CZE	0.75	4
COD	0.75	4
UGA	0.67	3
THA	0.67	3
SEN	0.33	3
SVN	1.00	3
TAN	1.00	2
GTM	1.00	2
TTO	1.00	2
CYP	0.50	2
RWA	0.50	2
UKR	1.00	2
LSO	1.00	2
BGD	0.50	2
MLI	1.00	2

S4: Association between governmental centrality and domestic ecosystem growth in climate-tech innovation networks

To evaluate whether governmental involvement is associated with broader domestic ecosystem growth, we regressed the increase in centrality of domestic organizations on the increase in governmental centrality across all countries but separately for each climate technology. As independent variable, we used the change in degree centrality of governmental organizations between the Pre-IRA period (01.2020–06.2022) and the Post-IRA period (07.2022–12.2024), defined as the change in the number of partnerships involving governmental actors headquartered in a given country. The dependent variable is the change in degree centrality of all domestic organizations headquartered in the same country, capturing the overall growth in national innovation activity.

To ensure reliability, we restricted the sample to country-technology combinations with at least 100 total partnerships across both periods. Regressions were estimated using ordinary least squares (OLS) via the statsmodels package in Python [72]. For each regression, we report the number of country observations, estimated coefficient, p-value, and R^2.

The results show a statistically significant relationship between increased governmental centrality and increased domestic ecosystem activity across all climate technologies (Supplementary Table S12). Coefficients range from 2.70 (concentrated solar) to 9.20 (battery), indicating that increased governmental involvement is associated with growth in domestic partnerships.

Table S12: Results of regressing increases in the centrality of domestic organizations in climate-tech innovation networks on increases in governmental centrality for each climate technology and with observations across countries.

Climate technology	**number of observations**	**Estimated coefficient**	p**-value**	R^2
Battery	58	9.20	2.82×10^{-22}	0.816
Biochar	19	3.51	2.45×10^{-2}	0.264
Biofuels	26	4.15	2.63×10^{-5}	0.528
Biogas	29	3.99	9.07×10^{-11}	0.794
Biomass	24	3.73	4.75×10^{-7}	0.692
Carbon Capture and Storage	36	4.54	3.34×10^{-13}	0.794
Concentrated Solar	15	2.70	4.94×10^{-4}	0.620
Direct Air Capture	13	6.83	1.93×10^{-10}	0.978
E-Fuels	21	5.34	3.17×10^{-8}	0.807
Electric Aviation	18	5.57	2.21×10^{-6}	0.763
Electric Shipping	29	4.76	2.51×10^{-7}	0.633
Electric Vehicles	60	5.09	3.36×10^{-24}	0.833
Fuel Cell Aviation	22	8.53	1.06×10^{-9}	0.850
Geothermal	27	5.57	5.85×10^{-10}	0.790
Heat Pumps	22	3.80	2.63×10^{-4}	0.494
Hydro Energy	26	3.31	1.04×10^{-3}	0.367
Hydrogen	59	5.84	1.49×10^{-30}	0.903
Marine Energy	33	7.46	4.06×10^{-17}	0.901
Nuclear Fission	19	2.95	4.28×10^{-13}	0.957
Nuclear Fusion	10	3.37	1.25×10^{-3}	0.747
Offshore Wind	36	6.57	3.41×10^{-18}	0.895
Railway	20	3.86	1.45×10^{-4}	0.561
Solar	83	5.63	1.29×10^{-27}	0.771
Sustainable Aviation Fuels	32	6.88	1.67×10^{-7}	0.604
Waste to Heat	23	4.95	1.32×10^{-10}	0.865
Wind (Onshore)	56	7.35	2.37×10^{-28}	0.897

S5: Implementation details of the relevance classifier for climate technologies

The relevance classifier for climate technologies is a sequence classifier based on supervised learning. As the underlying model, we used ClimateBERT [73], which is a domain-specific language model that has proven to perform well in the context of climate and energy [73, 74, 75]. ClimateBERT is based on a distilled variant of BERT [64, 76] and has been fine-tuned on 1.6 million additional climate-related texts. We fine-tuned the model for 50 epochs using a cross-entropy loss and the AdamW optimizer. Furthermore, we used a batch size of 64 and a learning rate of 1×10^{-6}. To avoid overfitting, the model with the highest validation score during training was selected.

As input for fine-tuning, we randomly sampled 10,000 LinkedIn posts from our initial set of organizations. After excluding reposts, which lead to multiple appearances of the same text, we

manually annotated 9,645 texts regarding their relevance for climate technologies and decarbonization, of which 2,482 of the texts were annotated as relevant. To counter this imbalance, we experimented with oversampling during training. However, this did not improve the results on the validation set and was therefore eventually discarded. We used a train/validation/test split of 0.85/0.075/0.075. As such, 724 annotated texts where used for testing the final performance of the classifier (Supplementary Table S25). The training, validation, and test data are provided in the Source Data.

Supplementary Figures

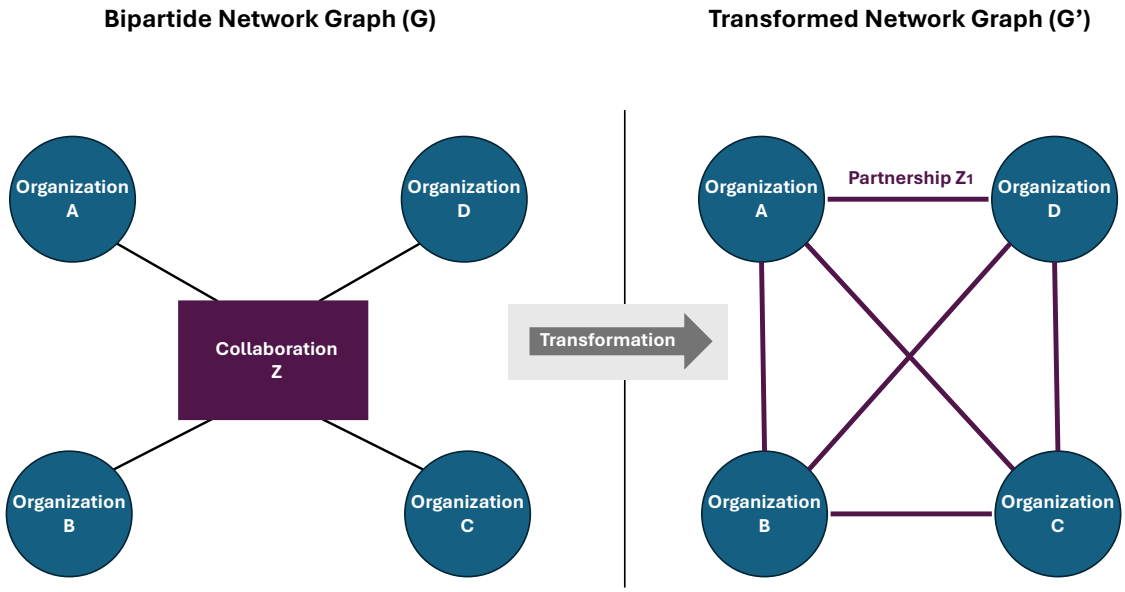


Fig. S4: Transformation from bipartide network graph G to transformed graph G'. In the first graph, organizations can only be linked to collaborations. In the second graph, we project these collaborations onto direct edges which we call "partnership". As illustrated, one collaboration can map onto multiple partnerships.

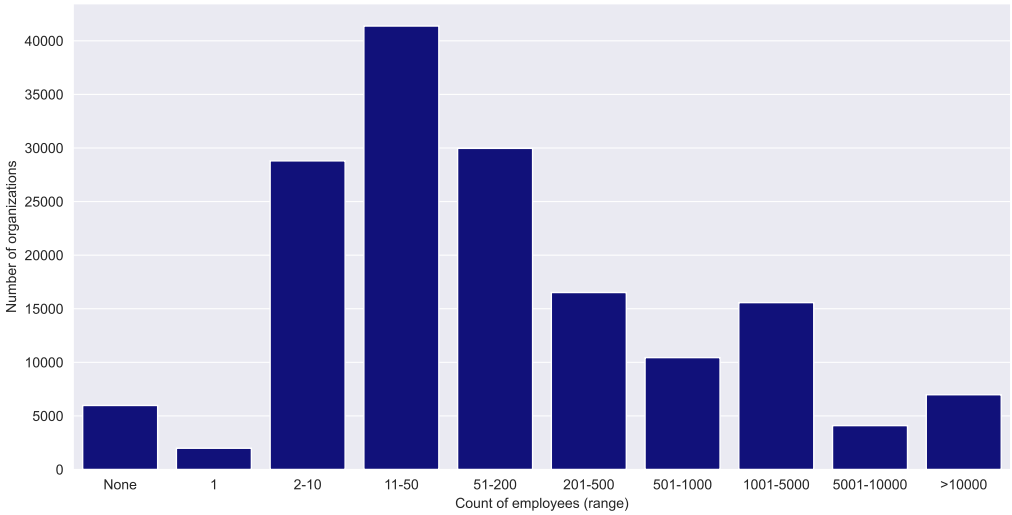


Fig. S5: Frequency of organizations across different counts of employees. These numbers are based on the ranges self-reported by the organization accounts on LinkedIn. Based on reported employment from LinkedIn profiles of members, all captured organizations jointly employ 128,296,940 people.

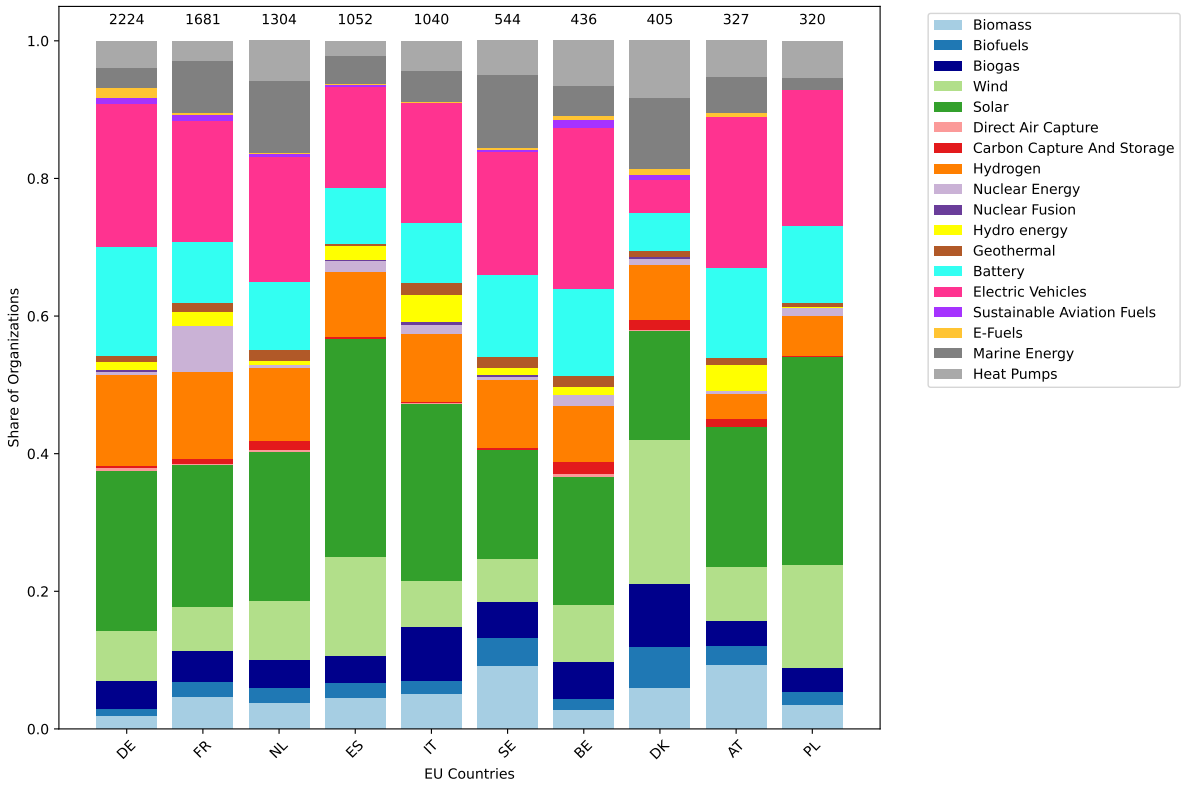


Fig. S6: Relative concentration of organizations in climate technologies by EU countries. Order is based on the absolute number of organizations specialized in climate technologies, which is reported on top of the bars.

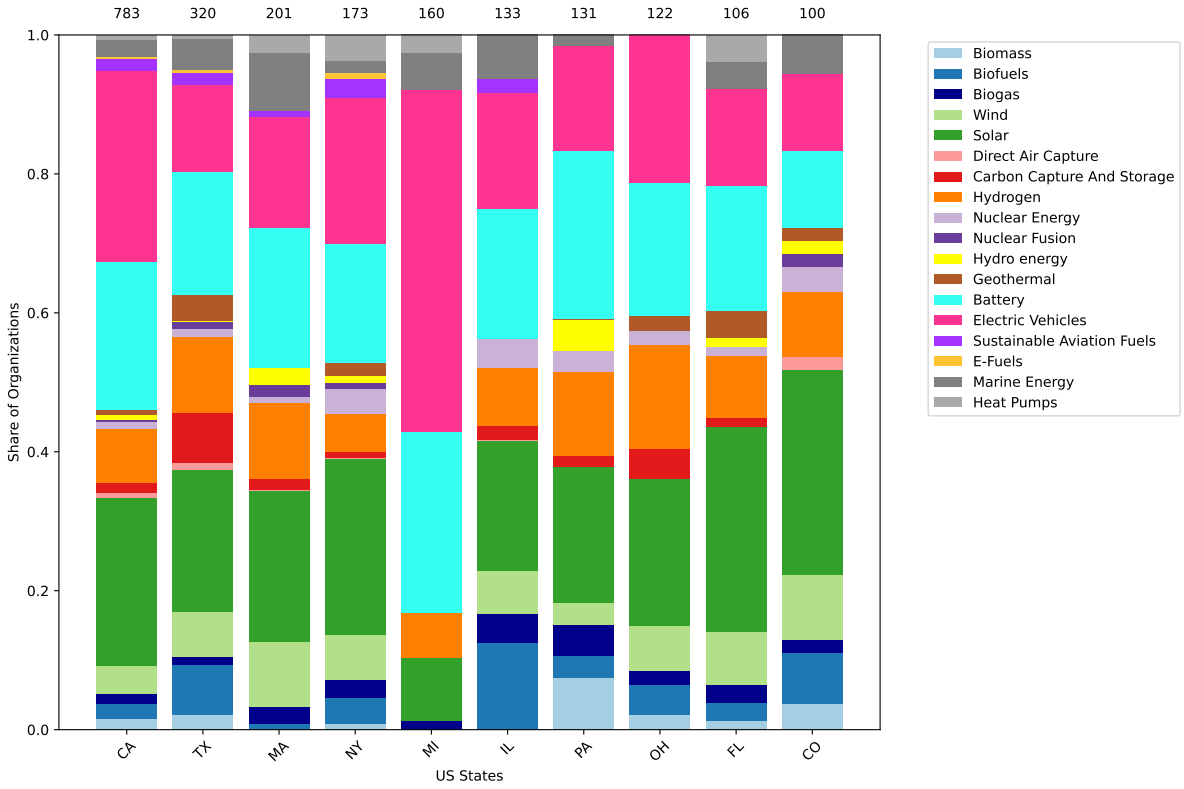


Fig. S7: Relative concentration of organizations in climate technologies by US states. Order is based on the absolute number of organizations specialized in climate technologies, which is reported on top of the bars.

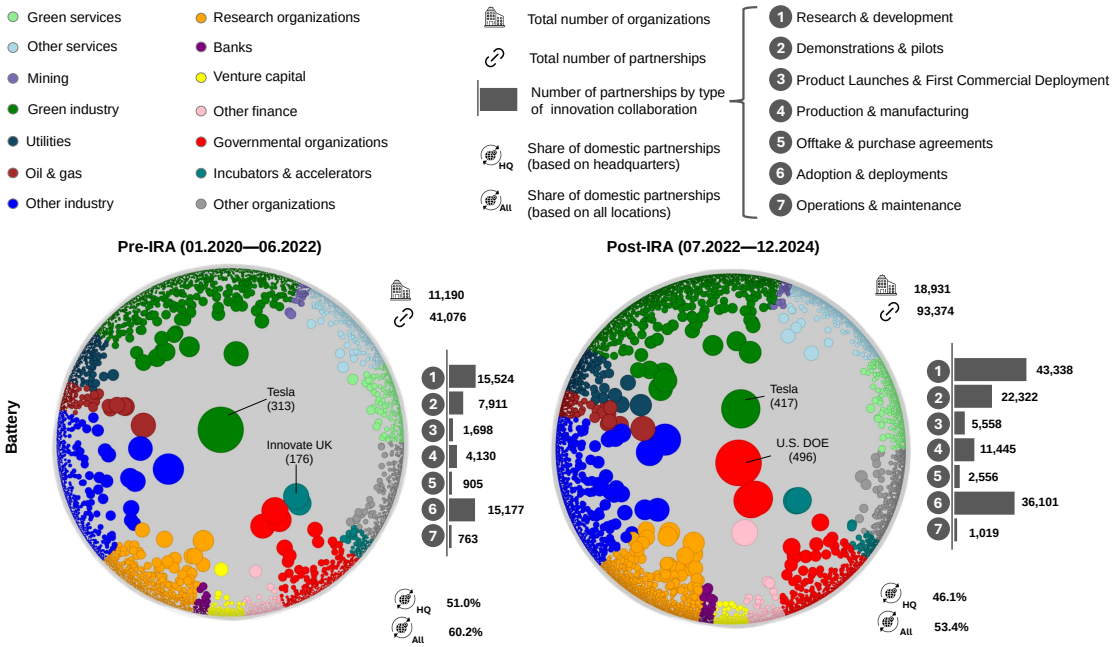


Fig. S8: **Structural evolution of the battery innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships''). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

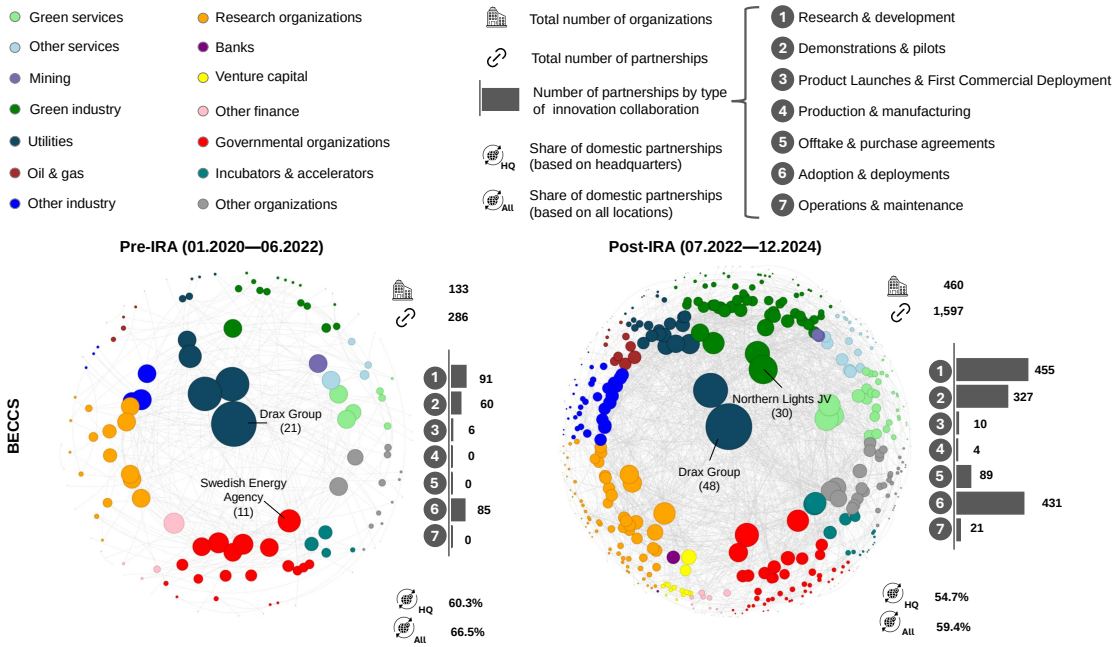


Fig. S9: **Structural evolution of the BECCS innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

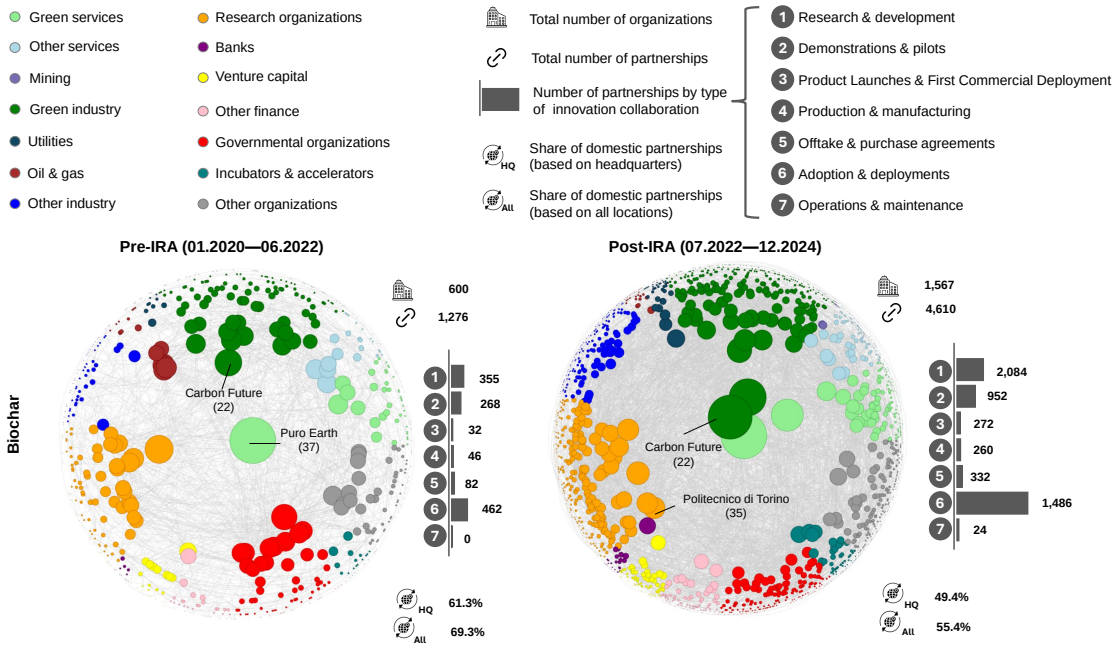


Fig. S10: **Structural evolution of the biochar innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

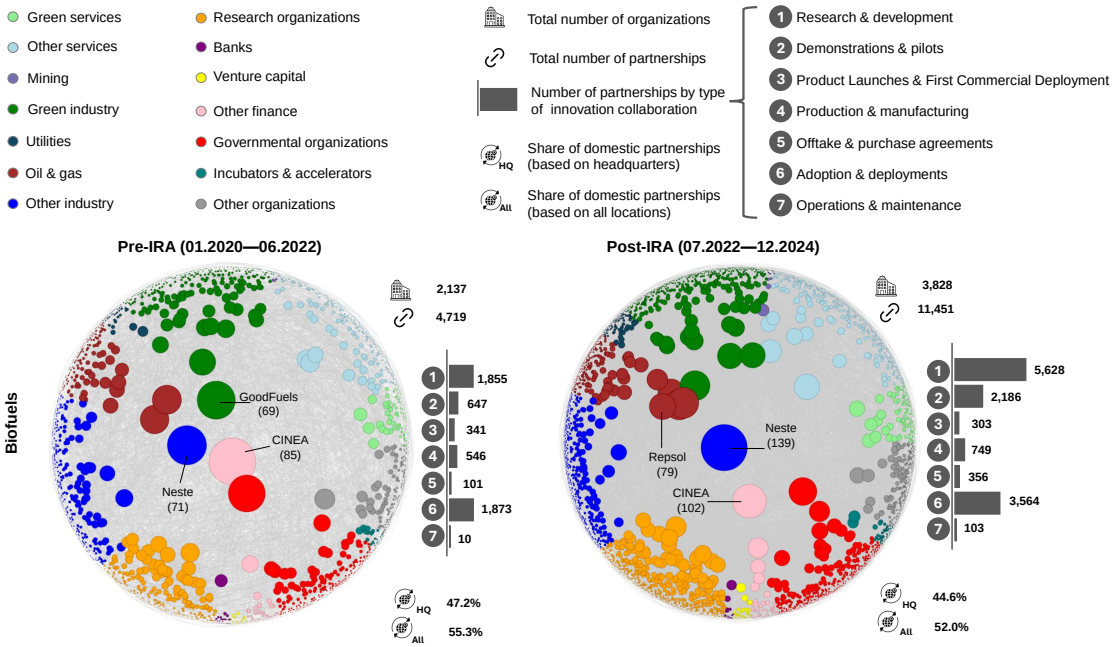


Fig. S11: **Structural evolution of the biofuels innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships''). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

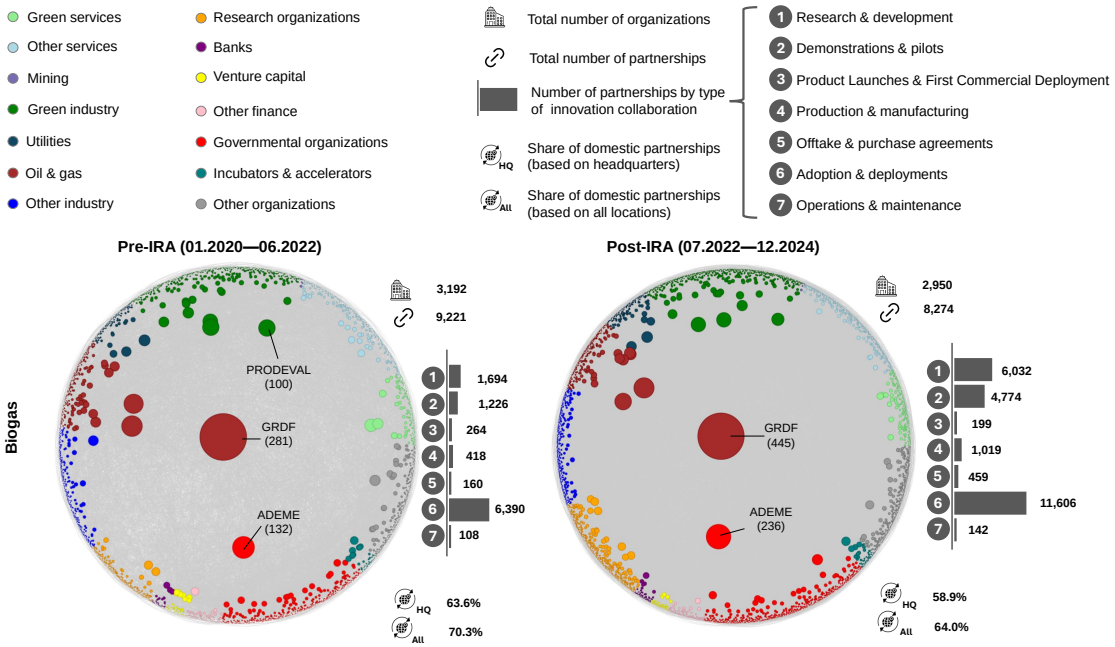


Fig. S12: **Structural evolution of the biogas innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships''). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

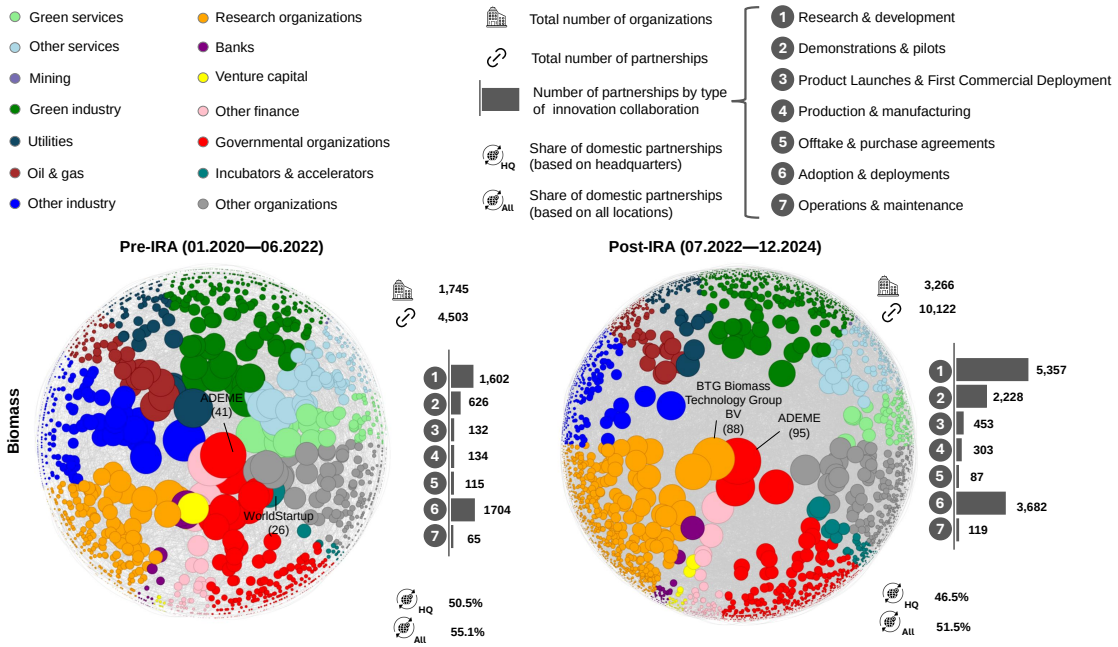


Fig. S13: **Structural evolution of the biomass innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

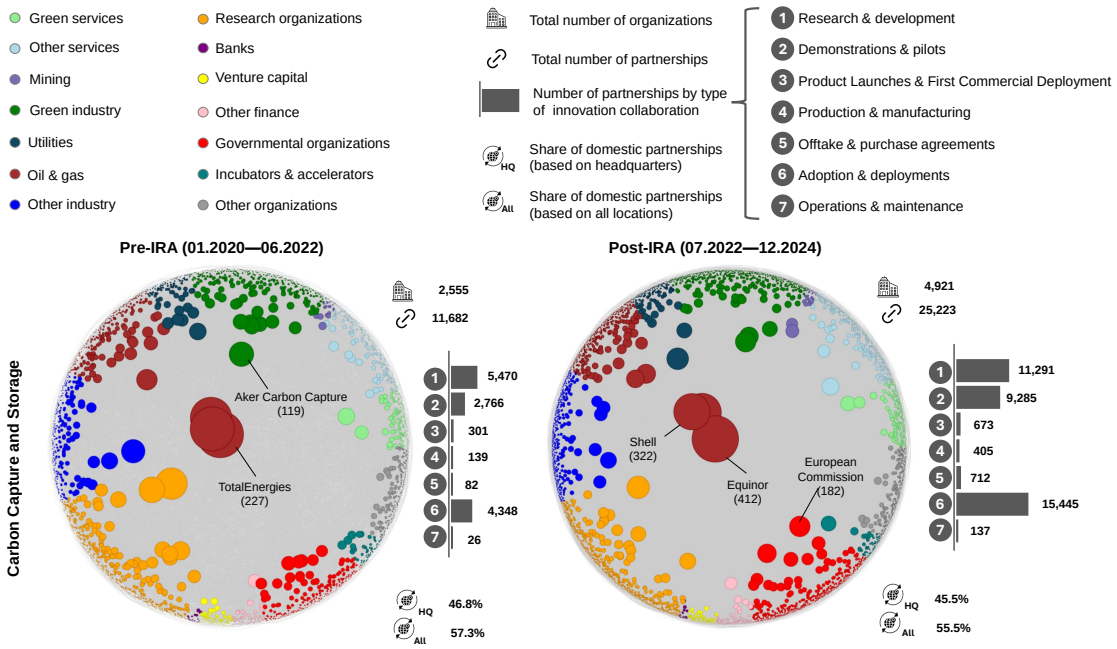


Fig. S14: **Structural evolution of the carbon capture and storage innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

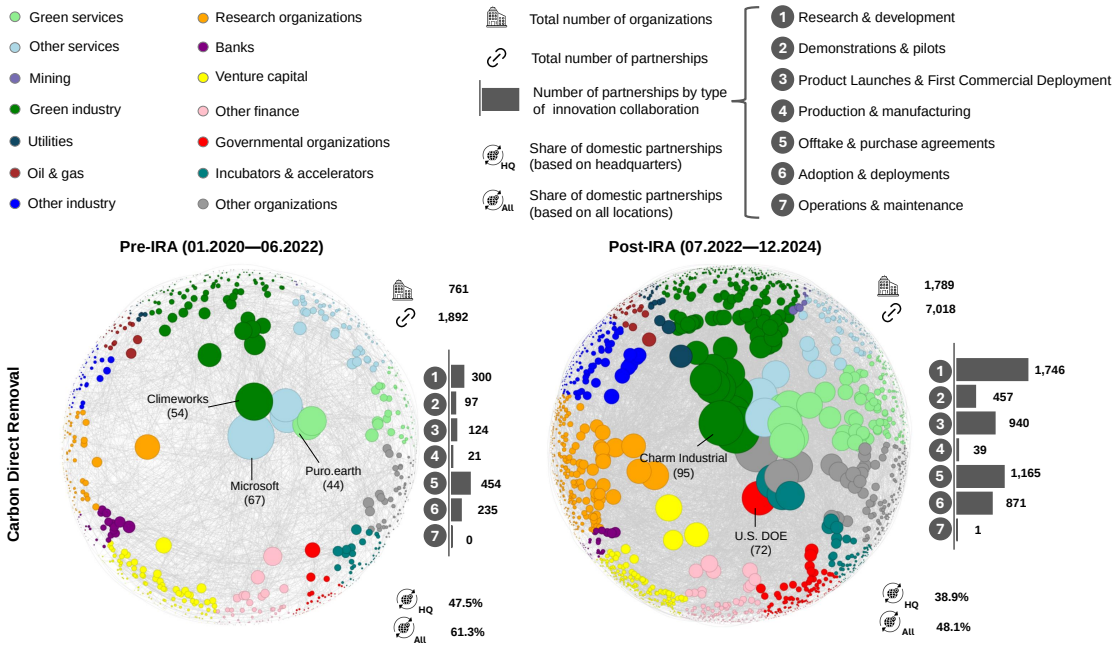


Fig. S15: **Structural evolution of the carbon direct removal innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

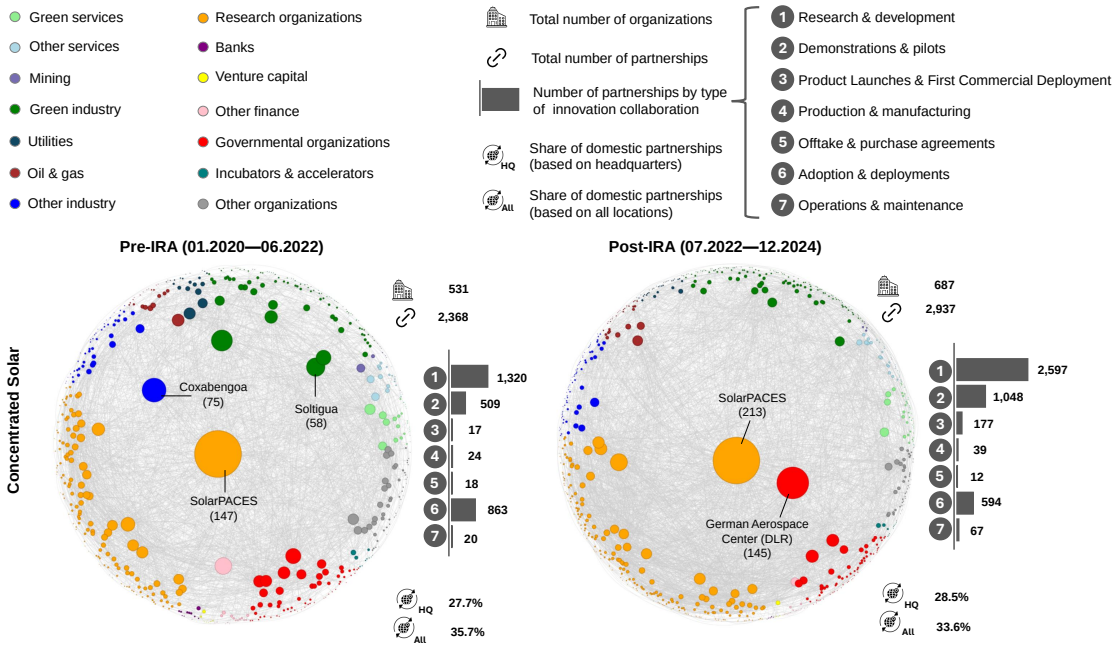


Fig. S16: **Structural evolution of the concentrated solar innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

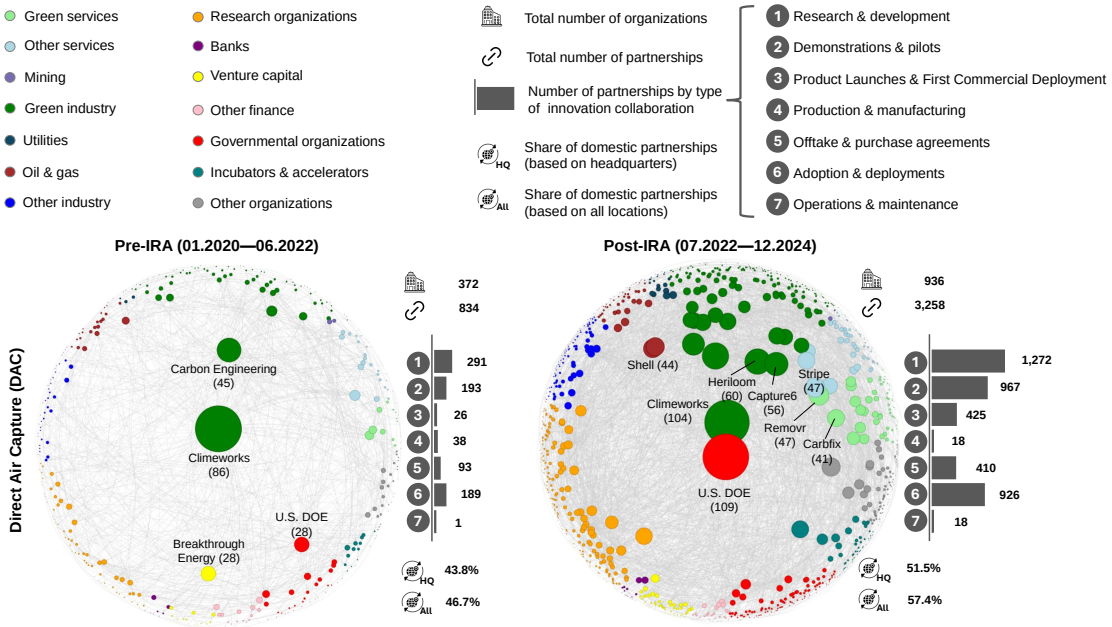


Fig. S17: **Structural evolution of the direct air capture (DAC) innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

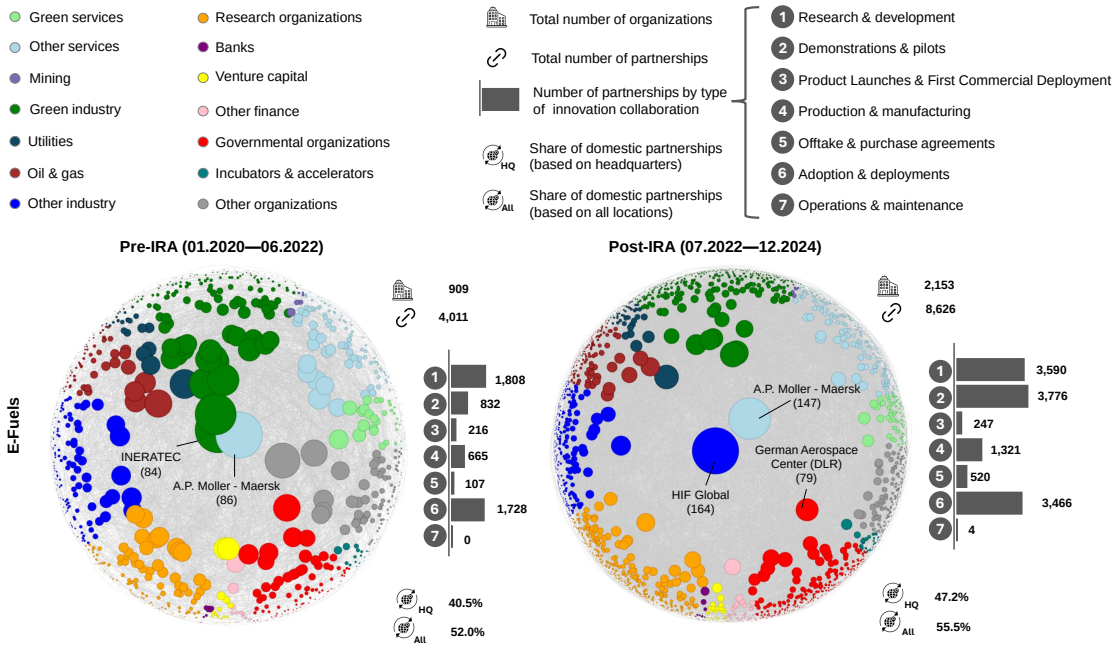


Fig. S18: **Structural evolution of the E-fuels innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships''). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

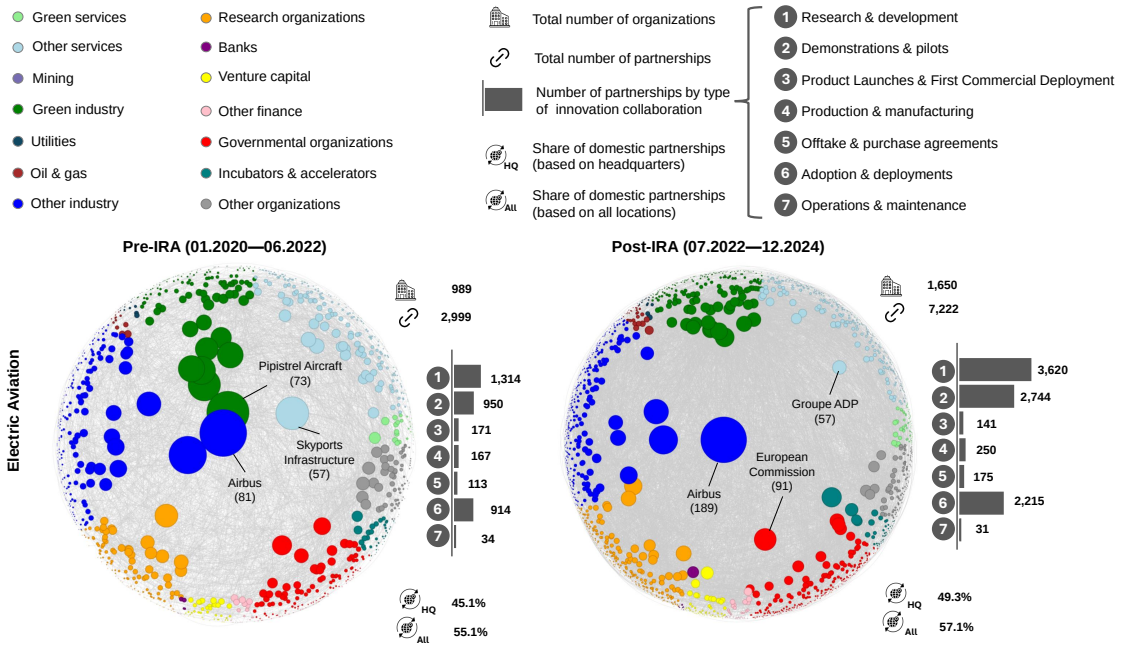


Fig. S19: **Structural evolution of the electric aviation innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

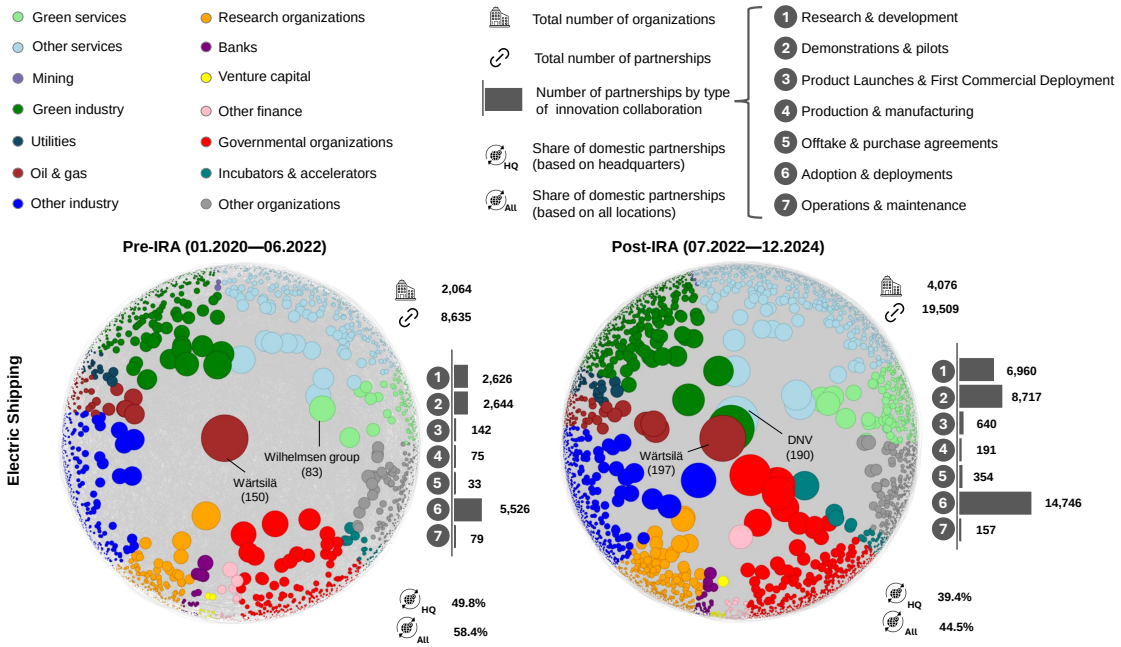


Fig. S20: **Structural evolution of the electric shipping innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

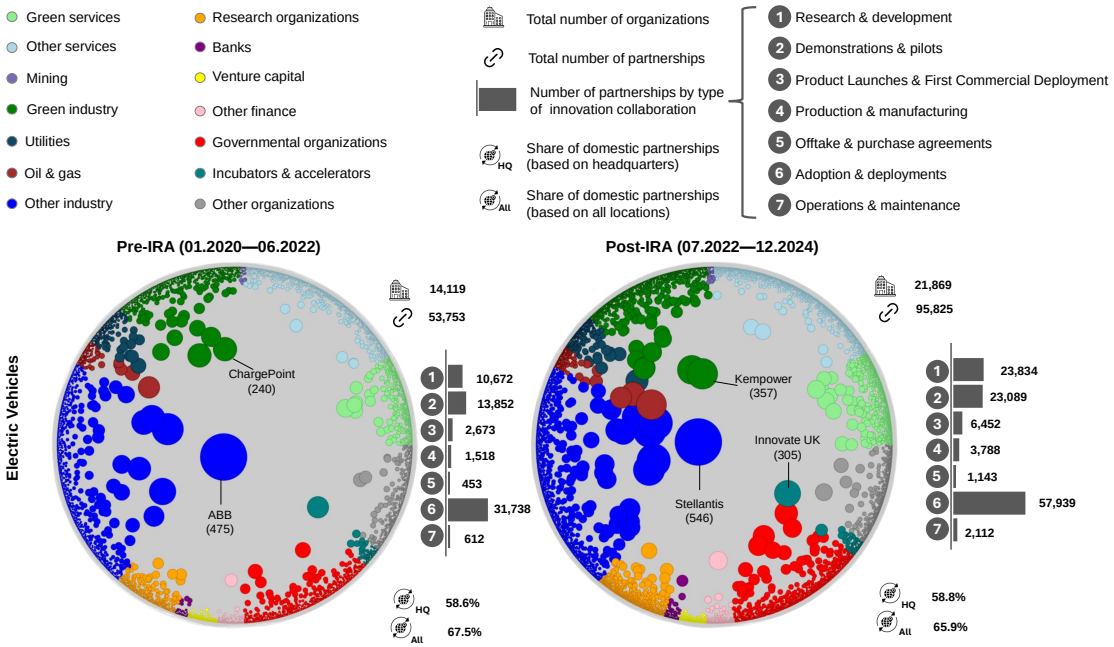


Fig. S21: **Structural evolution of the electric vehicles innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

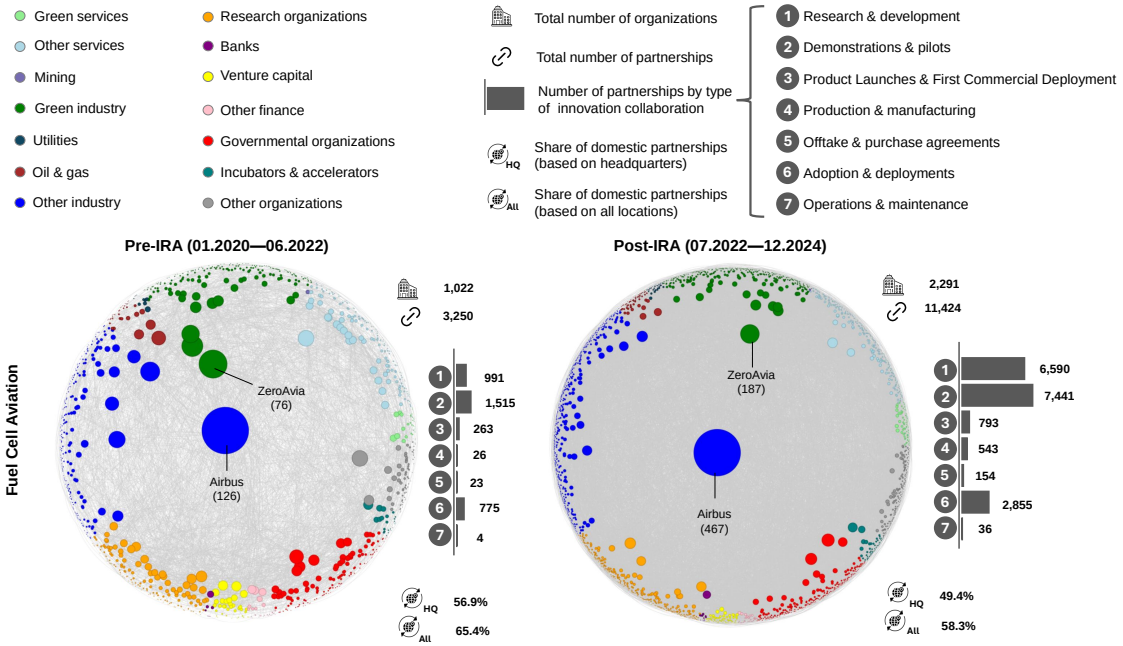


Fig. S22: **Structural evolution of the fuel cell aviation innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

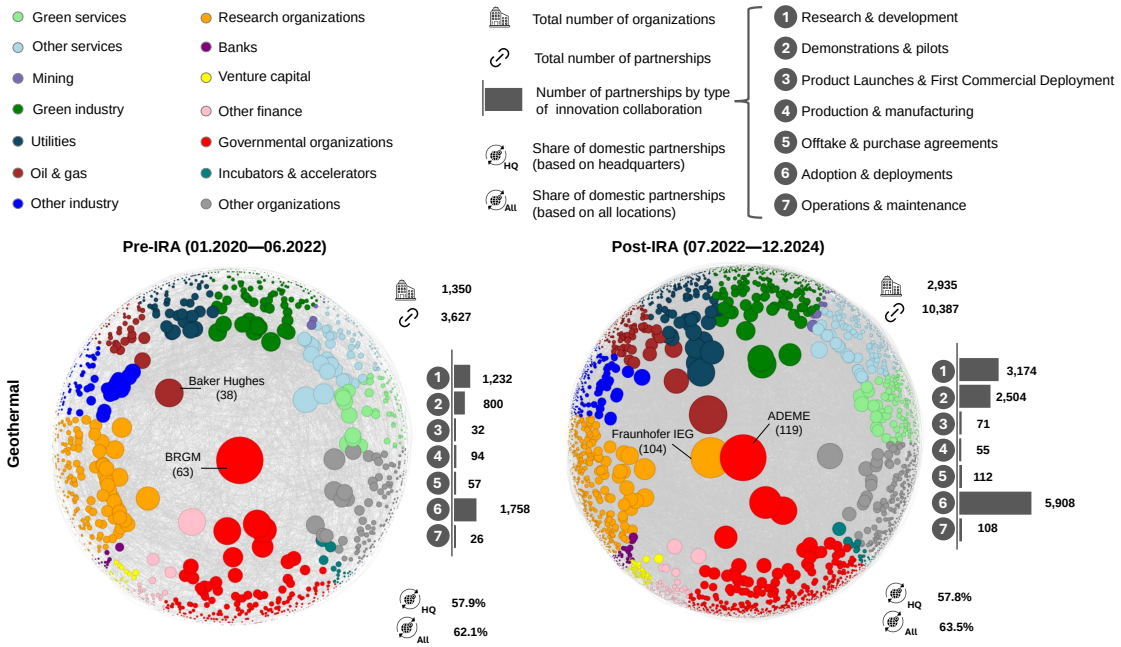


Fig. S23: **Structural evolution of the geothermal innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

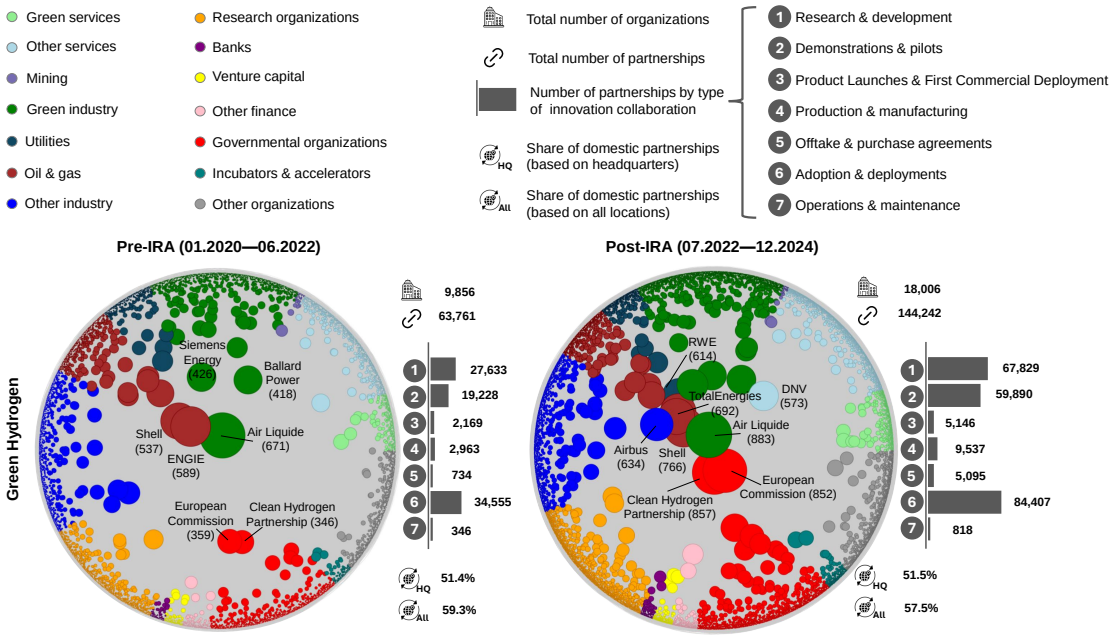


Fig. S24: **Structural evolution of the green hydrogen innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

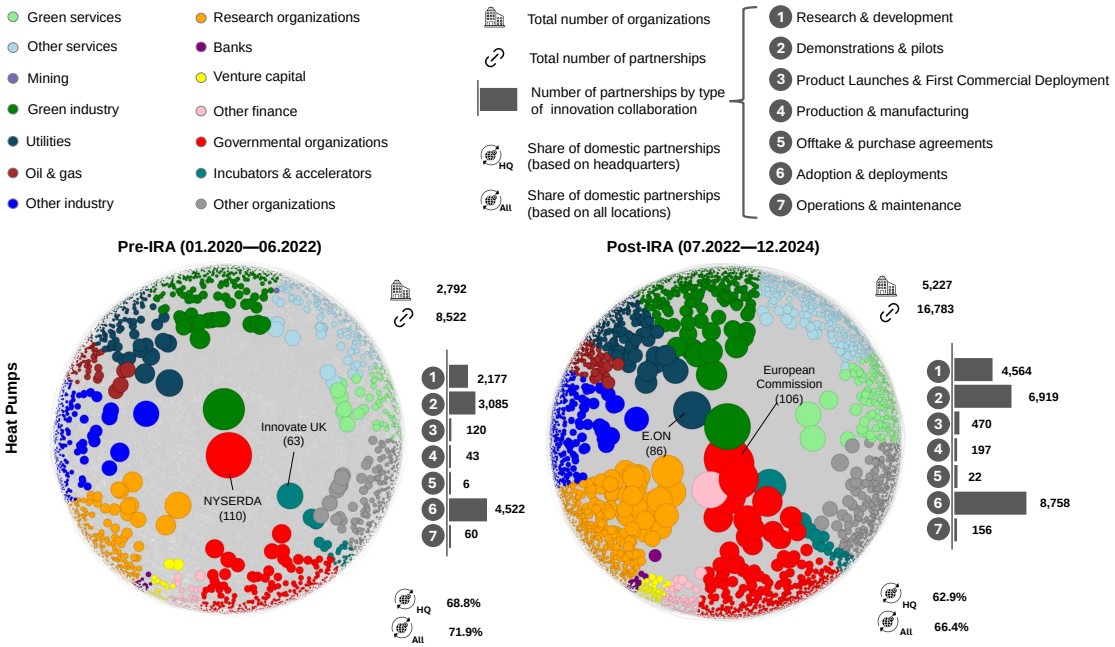


Fig. S25: **Structural evolution of the heat pumps innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

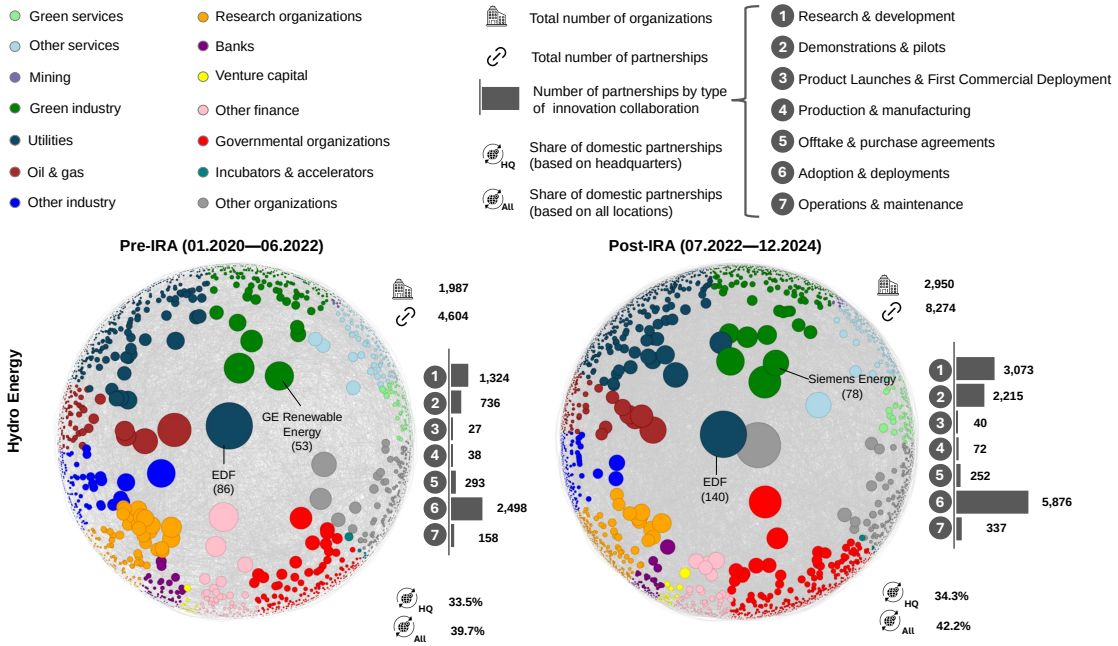


Fig. S26: **Structural evolution of the hydro Energy innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships''). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

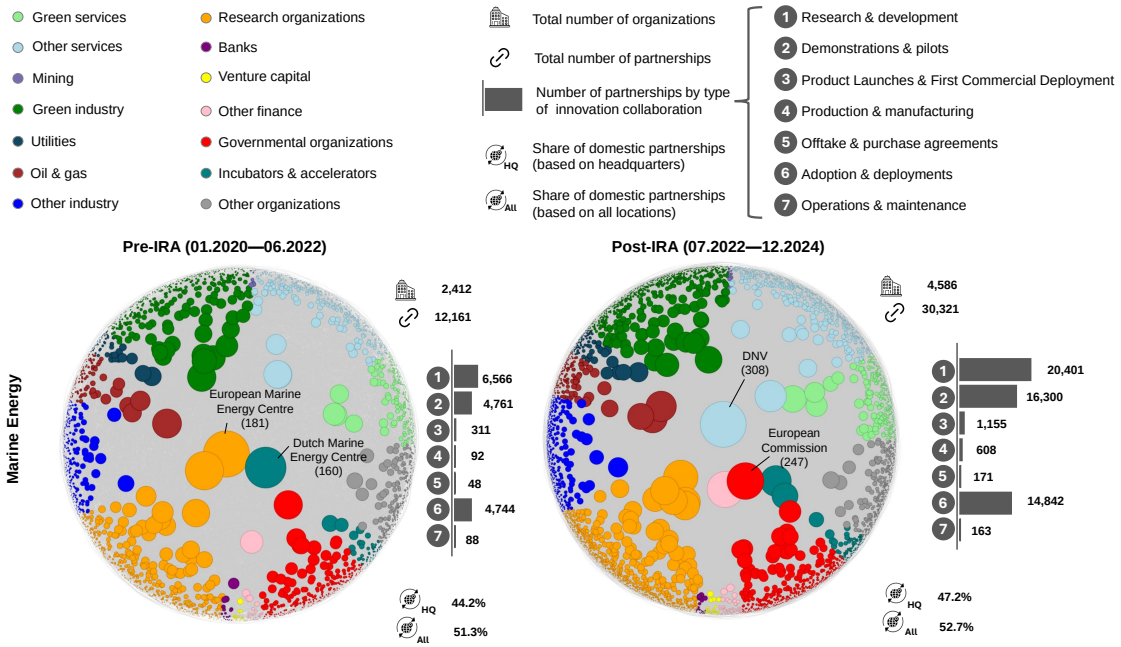


Fig. S27: **Structural evolution of the marine energy innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

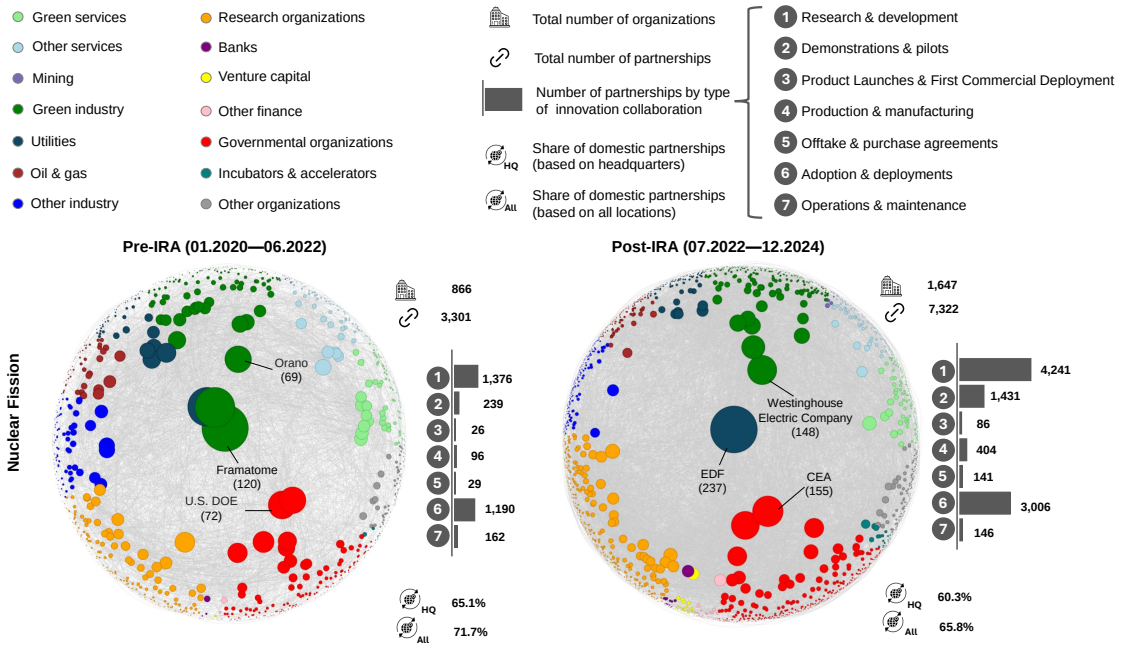


Fig. S28: **Structural evolution of the nuclear fission innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships''). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

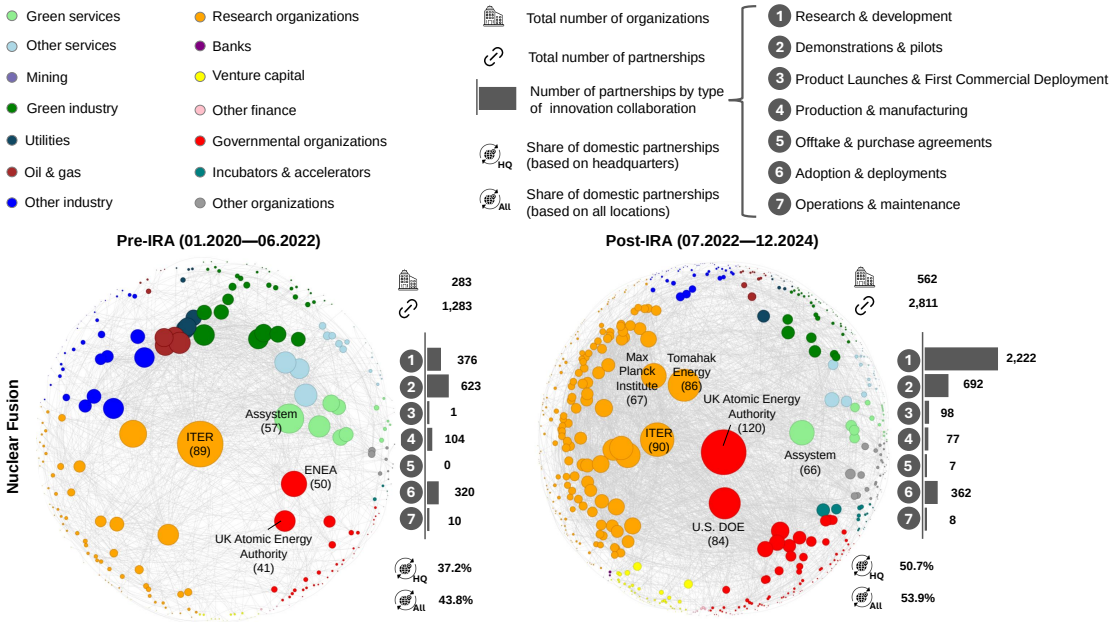


Fig. S29: **Structural evolution of the nuclear fusion innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

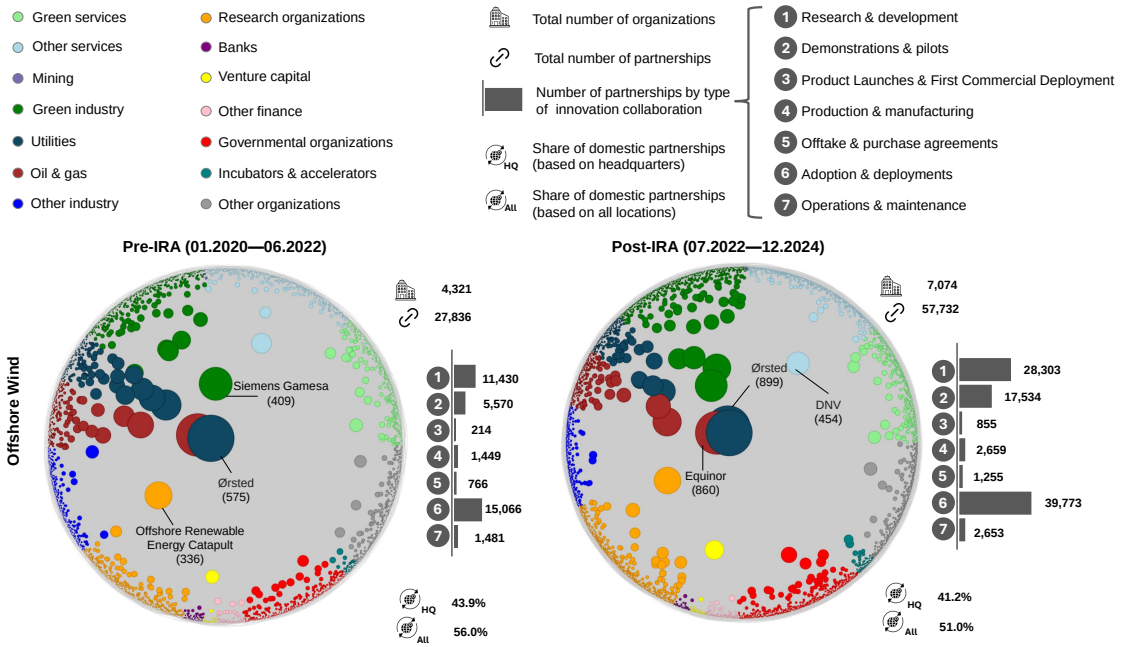


Fig. S30: **Structural evolution of the offshore wind innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

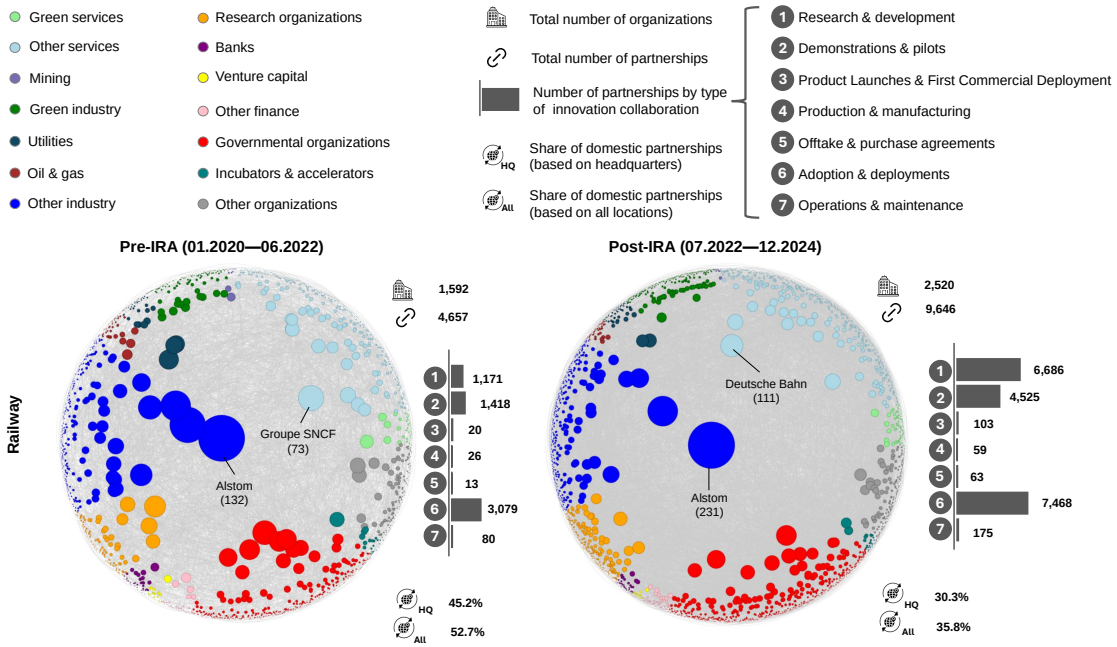


Fig. S31: **Structural evolution of the railway innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships''). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

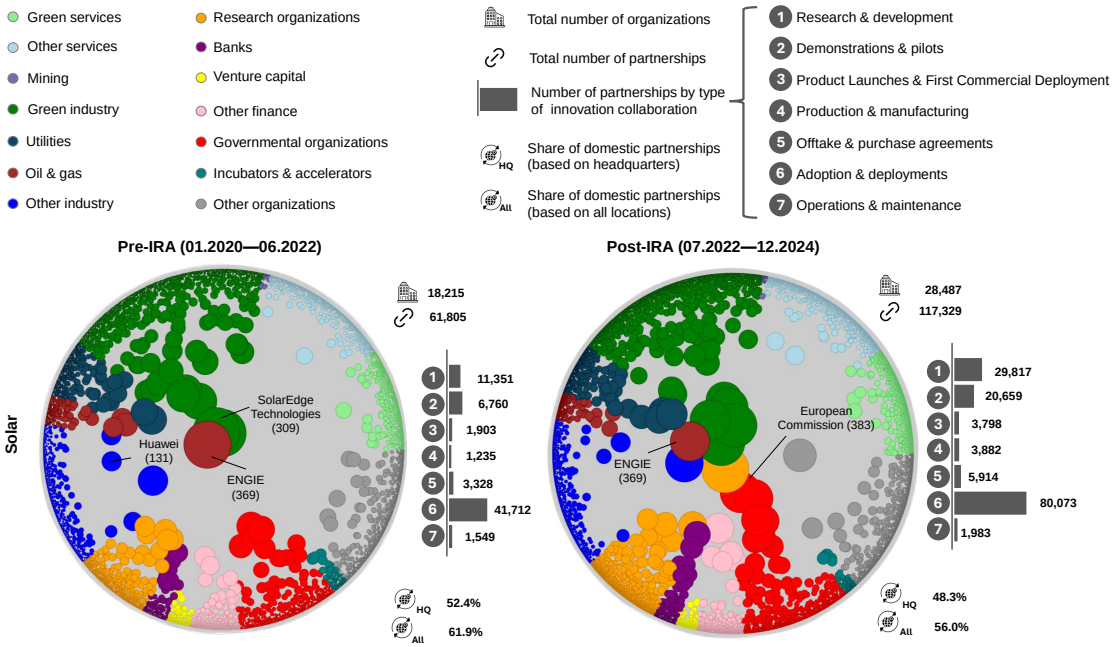


Fig. S32: **Structural evolution of the solar innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

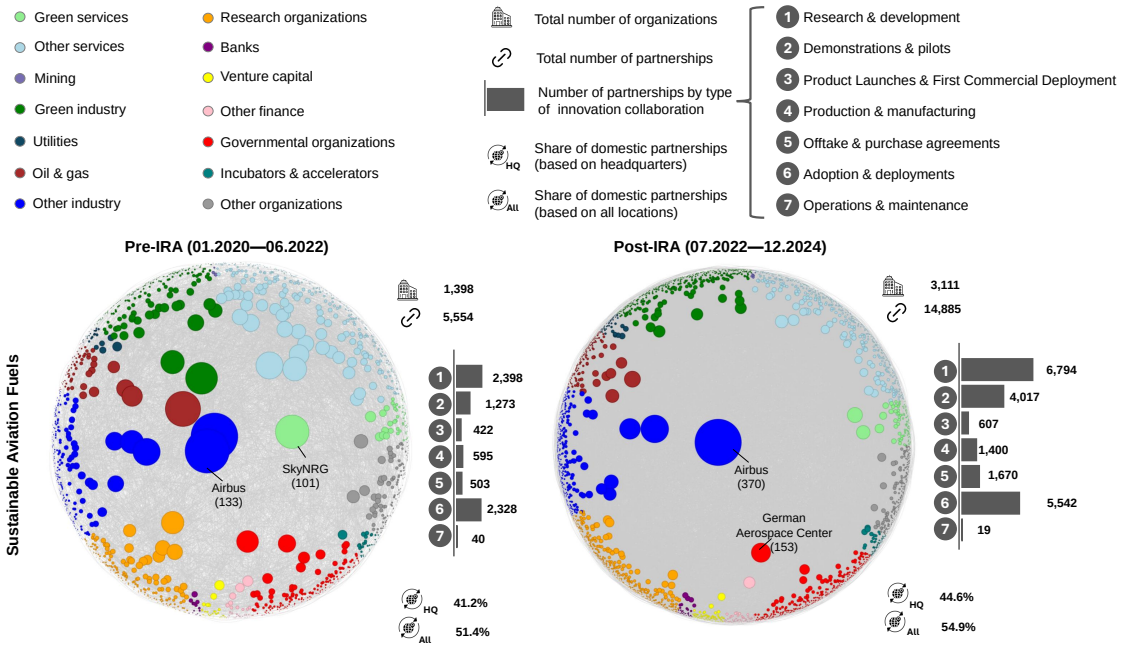


Fig. S33: **Structural evolution of the sustainable aviation fuels innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

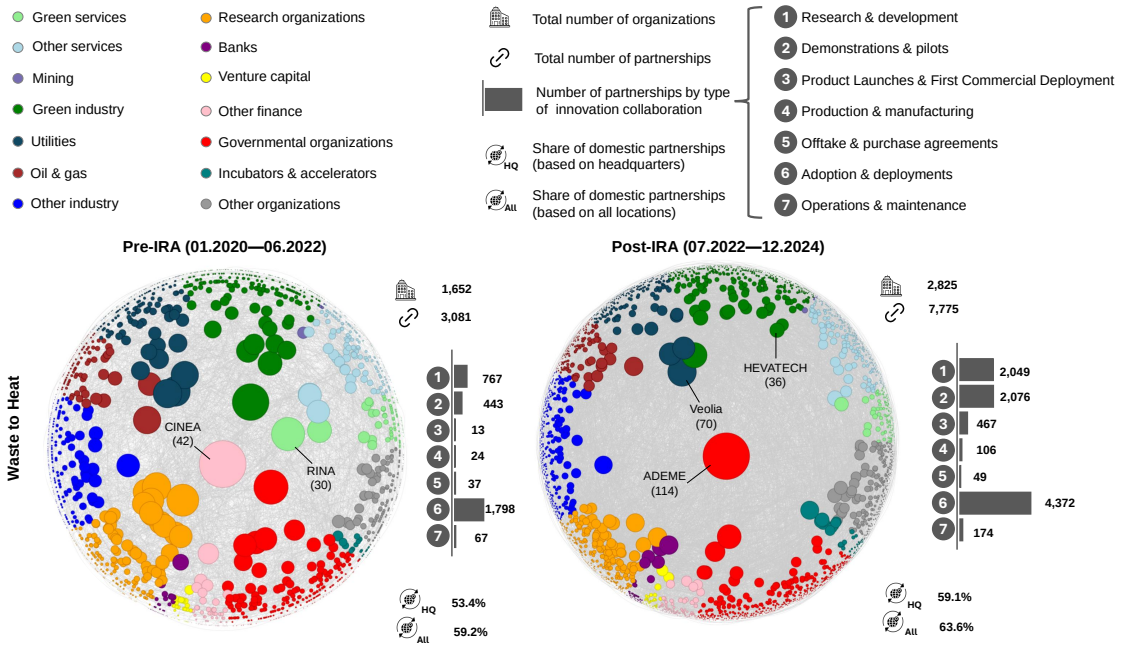


Fig. S34: **Structural evolution of the waste to heat innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

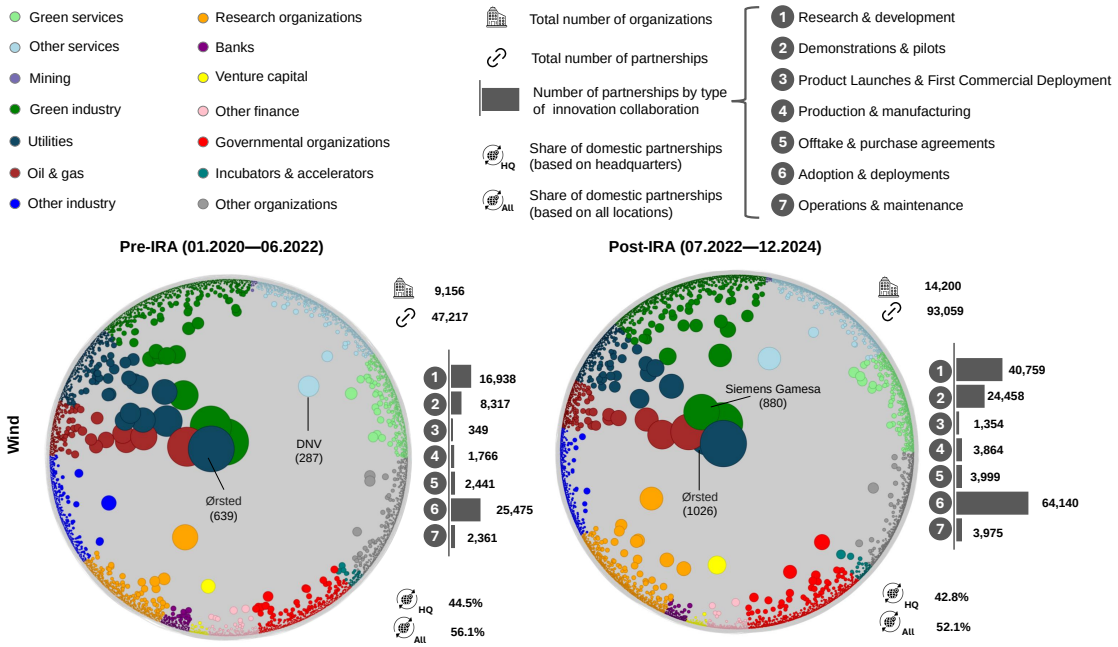


Fig. S35: **Structural evolution of the wind innovation network for the two periods before (Pre-IRA: 01.2020–06.2022) and after (Post-IRA: 07.2022–12.2024) the introduction of the inflation reduction act (IRA)**. As innovation collaborations can involve multiple organizations, we extract the direct edges between individual organizations from collaborations (called 'partnerships"). To prevent double counting from multiple announcements, partnerships between two organizations are only counted once per period. The size (radius) of organization nodes represents the degree centrality (i.e., the number of partnerships), with centrality values indicated in brackets for highlighted organizations. In the network plots, we only illustrate partnerships as a binary indicator (existing/not existing), while in the bars we count partnerships separately for each type of collaboration.

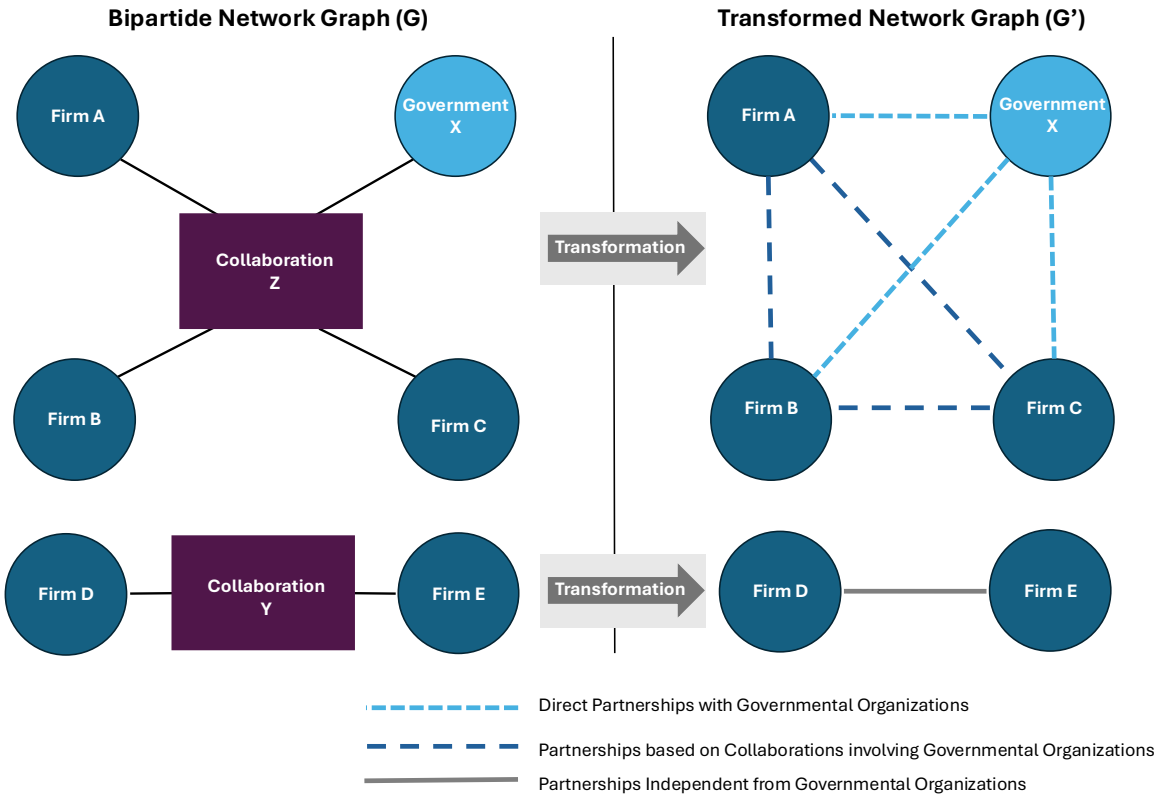


Fig. S36: Direct and indirect governmental involvement illustrated based on the transformations of two collaborations from their bipartide network graph G to the transformed graph G'.

Supplementary Tables

Supplementary Tables

Table S13: Breakdown of organizations by organization types. Note that organizations can be assigned to multiple categories (e.g., Manufacturer and Project Developer).

Type of Organization	Number	Share
Service Provider	58,376	0.36
Manufacturer	36,859	0.23
Governmental Organization	20,850	0.13
Non-Governmental Organization	9,038	0.06
Research Institute	8,009	0.05
Project Developer	7,689	0.05
Consulting	7,387	0.05
Media Firm	5,781	0.04
University	5,765	0.04
Other Financing Organization	5,639	0.03
Lobby Group	5,624	0.03
Event Organizer	5,515	0.03
Utility	4,900	0.03
Venture Capital	3,579	0.02
Accelerator / Incubator	2,652	0.02
Bank	2,209	0.01
International Organization	1,841	0.01
Mining	1,110	0.01

Table S14: Breakdown of organizations by sectors. Note that organizations can be assigned to multiple sector categories (e.g., Battery and Wind).

Sector	Number	Share
Climate technology sub-sectors		
Battery	4,398	0.027
Biofuels	1,310	0.008
Biogas	1,622	0.010
Biomass	1,954	0.012
Carbon Capture And Storage	725	0.004
Carbon Offsets	1,205	0.007
Direct Air Capture	146	0.001
E-Fuels	150	0.001
Electric Vehicles	7,891	0.049
Geothermal	894	0.006
Heat Pumps	1,773	0.011
Hydro Energy	1,486	0.009
Hydrogen	3,854	0.024
Marine Energy	2,475	0.015
Nuclear Fission	1,182	0.007
Nuclear Fusion	101	0.001
Other Carbon Removal	1,515	0.009
Other Energy Storage	5,041	0.031
Solar	13,297	0.082
Sustainable Aviation Fuels	326	0.002
Wind	5,439	0.034
Other Renewables	6,414	0.040
Fossil energy sub-sectors		
Coal	376	0.002
Gas	6,441	0.040
Oil	4,589	0.028
Other Fossil Energy	349	0.002
Other energy-related sub-sectors		
Electricity-grid	5,956	0.037
Energy General	6,333	0.039
Transport sub-sectors		
Automotive	7,362	0.046
Aviation	3,555	0.022
Railway	2,796	0.017
Shipping	3,955	0.024
Other Transport	7,691	0.048
Other relevant sectors		
Agriculture	5,031	0.031
Built Environment	6,032	0.037
Chemical Industry	2,602	0.016
Computer and Electronic Products	1,280	0.008
Iron and Steel	884	0.005
Military	1,202	0.007
Other Construction	12,778	0.079
Other ICT	9,916	0.061
Other Manufacturing	9,839	0.061
Raw Materials	1,247	0.008
Software	5,883	0.036

Table S15: Comparison in the number of organizations and partnerships of climate technology innovation networks between the Pre-IRA (01.2020–06.2022) and Post-IRA (07.2022–12.2024) periods. Technology readiness levels are based on evaluations by the International Energy Agency (IEA) [30]. Rows are ordered by the percentage increase in organizations. Note that the percentage increase in organizations across all climate technologies is lower than for individual climate technologies because new entrants of specific climate technology innovation networks are often already participating in other climate technology innovation networks.

		Pre-IRA (01.2020–06.2022)			Post-IRA (07.2022–12.2024)			Comparison (Pre-IRA vs. Post-IRA)	
Climate Technology	**Technology readiness level***	**Number of organizations**	**Number of partnerships**	**Density**	**Number of organizations**	**Number of partnerships**	**Density**	**Percentage increase organizations**	**Percentage increase edges**
Bioenergy with Carbon Capture and Storage (BECCS)	5	133	286	2.15	460	1,597	3.47	246%	458%
Biochar	Nan	600	1,276	2.13	1,567	4,610	2.94	161%	261%
Direct Air Capture (DAC)	6	372	834	2.24	938	3,267	3.48	152%	292%
E-Fuels	6	909	4,011	4.41	2,153	8,626	4.01	137%	115%
Carbon Direct Removal (Other Solutions)		761	1,892	2.49	1,789	7,018	3.92	135%	271%
Fuel Cell Aviation	6–7	1,022	3,250	3.18	2,291	11,424	4.99	124%	252%
Sustainable Aviation Fuels (SAFs)	7–8	1,398	5,554	3.97	3,111	14,885	4.78	123%	168%
Geothermal	6–7	1,350	3,627	2.69	2,935	10,387	3.54	117%	186%
Electric hipping	9	2,064	8,635	4.18	4,076	19,509	4.79	97%	126%
Nuclear Fusion	1–3	285	1,286	4.51	562	2,811	5.00	97%	119%
Carbon Capture and Storage (CCS)	7–8	2,555	11,682	4.57	4,921	25,223	5.13	93%	116%
Nuclear Fission	10–11	866	3,301	3.81	1,647	7,322	4.45	90%	122%
Marine Energy	7–8	2,412	12,161	5.04	4,586	30,321	6.61	90%	149%
Biomass	10	1,756	4,525	2.58	3,293	10,458	3.18	88%	131%
Heat Pumps	9	2,792	8,522	3.05	5,227	16,783	3.21	87%	97%
Hydrogen	9	9,856	63,761	6.47	18,030	145,089	8.05	83%	128%
Biofuels	9–10	2,137	4,719	2.21	3,828	11,451	2.99	79%	143%
Waste to Heat	Nan	1,652	3,081	1.87	2,825	7,775	2.75	71%	152%
Battery	9	11,190	41,076	3.67	18,931	93,374	4.93	69%	127%
Electric Aviation	4–5	989	2,999	3.03	1,650	7,222	4.38	67%	141%
Railway	11	1,529	4,657	3.05	2,520	9,646	3.83	65%	107%
Offshore Wind	8–10	4,321	27,836	6.44	7,074	57,732	8.16	64%	107%
Biogas	8–9	3,192	9,221	2.89	5,194	19,147	3.69	63%	108%
Solar	10	18,215	61,805	3.39	28,487	117,329	4.12	56%	90%
Wind (Onshore)	10	9,156	47,217	5.16	14,200	93,059	6.55	55%	97%
Electric Vehicles	8–9	14,119	53,753	3.81	21,869	95,825	4.38	55%	78%
Hydro Energy	11	1,987	4,604	2.32	2,950	8,274	2.80	48%	80%
Concentrated Solar	9–10	531	2,368	4.46	687	2,937	4.28	29%	24%
All		49,727	295,433	5.94	74,030	570,389	7.70	49%	93%

Table S16: Details of the attribution of individual organizations to organization groups based on their organization type and sectors.

Group of organizations	**Rule for inclusion**
Green services	Organization type includes ”Service provider” and Sector includes a climate technology (e.g., solar, wind, batteries).
Other services	Organization type includes ”Service provider” and Sector does not include a climate technology.
Mining	Organization type includes ”Mining”.
Green industry	Organization type includes ”Manufacturer” or ”Project developer” and Sector includes a climate technology.
Utilities	Organization type includes ”Utility”.
Oil & gas	Sector includes ”Oil” or ”Gas”.
Other industry	Sector includes ”Manufacturer” or ”Project developer” and is not attributed to any of the upper groups of organizations.
Research organizations	Organization type includes ”Research institute” or ”University”.
Banks	Organization type includes ”Bank”.
Venture capital	Organization type includes ”Venture capital”.
Other finance	Organization type includes ”Other financing organization”.
Governmental organizations	Organization type includes ”Governmental organization”.
Incubators & accelerators	Organization type includes ”Incubator” or ”Accelerator”.
Other organizations	Every organization not mapped to any other group of organizations.

Table S17: **Types of collaborations.** Note that each post can be assigned to types of collaborations.

Type of collaboration	Description	Exemplary posts		
Research and Development	Research and development activities to improve or create new technologies, processes, and applications.	we are partnering with valeo and siemens eautomotive to develop and manufacture a new-generation automotive electricmotor in france, at the cléon plant, starting 2027.	the announcement of our partnership with brek electronics to develop a first-of-its-kind bi-directional ev charger for north america, as seen on power magazine: https://bit.ly/3lexuc0	the future of sustainable mobility also passes from innovative and ecological fuels, such as the r33 bluediesel: developed by volkswagen agcce, is composed of 33% of waste materials and breaks down co2 emissions up to 20%. find out more on a way: https://bit.ly/2essefp
Demonstrations and Pilots	Activities to test new or improved technologies, processes, and applications in real-world environments.	this project, the first official project of the northern cheyenne office of renewable energy follows a series of demonstration projects, including a 100kw system on the roof of the little wolf capitol building. (...)	kallista energy inaugurates its pilot charging station in normandy, with the abb terra 360 terminals, the most powerful electric terminals in france.this station is the first milestone of kallista energy in the deployment ofits network of 90 very high power charging stations through france, (...).	katapult portfolio company solarduck will build japan's first offshore floating solar demonstrator in tokyo bay. amazing workkoen burgersand team!
First commercial deployments and product launches	Activities towards first commercial deployments or product launches of new or improved technologies, services, and applications.	tata motors has announced that the nexon ev will be the first electric vehicle with tata motors' cutting-edge ziptron technology. david hudson, head of vehicle and powertrain engineering, said: "i am delighted to be able to share the news about the nexon ev being launched in the indian market (...)."	following the launch of neste my renewable diesel™ on the belgian market in july, neste has now entered a partnership with q8 to offer the product on 7 q8 stations during this year.neste my renewable diesel is a premium diesel made entirely from renewable raw materials.	we've been awarded a grant by net zero technology centreto advance the commercialization of our pseudo dry gas technology. find out more: https://okt.to/x3rwhd
Production and Manufacturing	Production and manufacturing of technologies and parts without direct deployment or end-consumer sales. This includes the construction of new manufacturing plants or collaborations for large-scale production.	proud to be working with the team at amte power on this exciting projectto scale up capacity for battery cell production in the uk!	with open arms, we welcome the battery factory from volvo carsoch northvolt to gothenburg - at gothenburg energy, together with a number of players in the city, we have worked hard for a long time to produce an attractive offer for northvolt /volvo.	we are excited to get to work on our exciting new project in cooperation with engie , neste , paul wurth and cea . the 2.6mw high-temperature electrolyserwill support the production renewable fuelsat neste 's rotterdam refinery. (...)
Offtake Agreements and Futures	Contracts for future purchase of goods or services, often used to secure demand for energy or technology products.	rockwell automation, inc. announced an agreement with 1pointfive to purchase carbon dioxide removal credits from its direct air capture (dac) facility under construction in texas. carboncapture directaircapture carbonremoval cdr https://bit.ly/3t2tvlx	as part of our ambition to be a net-zero emissions company by 2050, we're taking steps to reduce our environmental impact while continuing to produce the commodities that advance everyday life.that's why we're proud to announce that our asturiana de zinc operations – europe's biggest zinc producer – has signed a long-term agreement with edp renewables for the supply of renewable electricity from wind. the agreement will avoid 63,000 tons of co2 emissions annually until 2040.	aemetis announced that an offtake agreement with qantas group for 35 mmg of blended sustainable aviation fuel (saf) to be delivered over the seven-year term of the agreement. https://lnkd.in/djykyjtm
Adoption and Deployments	Uptake of technologies by customers or users, including installations, implementations, and integrations.	kallista energy 's first wind park in the netherlands is commissioned!the 8 wind turbines of windpark oostflakkee, in goeree-overflakkee, are now up and running! they will produce enough renewable energy to supply the equivalent of 35,000 households every year.	last year, grid installed a solar microgrid with help of nepali women in solar trainees in jodhgaun, nepal, bringing electricity to 100 households.thanks to sponsors @ google cloud for supporting and visiting the installation.winnie lamxavier riley	powered by ballard's heavy-duty fuel cell modules, regionalverkehr köln gmbh(rvk), cologne's regional transport company, successfully operates europe's largest fleet of zeroemission, hydrogen fuelcellbuses today. the 52-bus fleet comprises buses from van hooland solaris bus & coach , with an additional order of the latest 20 solaris and 20 wrightbus units. (...)

Operations and Maintenance	Operation and maintenance of technologies that are already deployed and in use.	amazing news just before the summer holiday: we are happy and proud to share with you that parkwind has trusted us with a service contract on the offshore wind park arcadis ost 1 in the baltic sea.the contract covers 2022-2027 and contributes to the realisation of our strategic ambition of increasing revenue from service assignments." (...)	blink's wholly owned european subsidiary, blue corner, has signed a contract to sell and operate ev charging stations at theku leuvencampuses across belgium. this exclusive, four-year sales contract also includes a 10-year service agreement for the operation of the charging stations.	a three-and-a-half-year contract has been signed between moray west offshore windfarm and fern communications limited to supply, install, support and maintain the moray west communications system.read more... http://ow.ly/iewu50l7mpa
Grants	Non-repayable financial awards typically issued by governments or foundations to support R&D, deployment, or capacity building.	energistyrelsen has awarded the h2res project a grant for renewable hydrogenproduction & distribution at the ørsted plant in avedøre. we're excited to be part of this, delivering the hydrogen station/distribution solution. http://bit.ly/h2res	GE Vernova's Advanced Research business has been selected by the U.S. DOE ARPA-E to receive a grant as part of their new H2SENSE Exploratory Topic, aimed at supporting innovative approaches for H2 gas detection and quantification across the H2 supply chain.	h2020project spotlight: the sintef eu funded h2020energy 4refinery project brings next the generation of biofuelsby integrating bioliquidsinto existing refinery processes.to find out more about this project: https://europa.eu/!vt49mt
Equity Investments	Funding for companies in exchange for ownership shares.	less than two years after its creation and following the completion of a first seed round of funding worth €5.2m,ze energy, a french independent renewable energy producer operating hybrid solar power plants (photovoltaic and storage), announces the completion of a €40m series b round of funding that will help bring the company to new heights. backed by its initial investors, demet er, htgf, everwatt andze way invest, the company can now count on the support of marguerite and the groupe sorégies. (...)	today marks the start of a new era in our company's history: we are thrilled to announce the successful completion of our series d financing round, securing €109 million ($125 million) of new funding from a consortium of investors led by lightrock and planet first partners, and including carbon direct capital management, hydrogenone capital llp , and existing shareholders. (...)	we are excited to announce that our partner company upowa , cameroon's leading access to energy provider, has closed their series a2 with a eur 2.5m investment.the investment was led by the uk government-backed repp (renewable energy performance platform) together with french family officecolam.impact and lita.co.to read the full article: https://lnkd.in/gitzx8u
Loans	Debt financing arrangements, including concessional loans or infrastructure finance for energy and climate projects.	kyotherm has secured €17m in long-term senior debt from crédit agricole transitions & energies to finance a portfolio of 25 energy efficiency projects (...)	earlier this week the facility for energy inclusion signed its inaugural mini-grid transaction to provide usd 7.5 million senior debt to mysolgrid zambia (formerly powercorner zambia) to construct 60 mini-grids which (...)	Bringing a retired nuclear power plant back to life for the first time in American history! Today, LPO and the U.S. Department of Energy (DOE) announced the closing of a $1.52 billion loan guarantee to Holtec Palisades to help finance the restoration and resumption of service of an 800-MW nuclear generating station in Covert Township, Michigan. (...)
Other Unspecified Finance	Financial support not fitting into equity, grants, or loans, including bonds, credit lines, and insurance mechanisms.	All Onis pleased to announce that 22 wholly Nigerian owned enterprises have been shortlisted for the 2020 USADF – All On Nigeria Off-Grid Energy Challenge.(...)	we mark a new milestone for mitsubishi power americas ' advanced clean energy storage greenhydrogenhub in utah with a us $500m conditional commitment from the u.s. department of energy. (...)	Scottish technology-led producer of green chemicals Celtic Renewables has launched its latest crowdfunding campaign with Crowdcube. https://lnkd.in/eyNJQVKT
Spin-offs	New independent companies created from existing organizations. This includes university spin-offs.	a research team from max planck society has developed a high-speed metallic fleece that promises progress in energy density, loading rates and safety of batteries. meanwhile, the spin-off company batene gmbh markets the technology as the sole license carrier.	oxccu tech ltd- a spinoff from the university of oxford have developed a very cost-effective procedure for the production of synthetic fuels	maxsolar is excited to announce the spin-off of its community solar management business. formerly known as maxsolar community , the new stand-alone business will be named metrosun community .
Incubator/ Accelerator Programs	Support programs designed to help new startups through training, office space, and other support.	halliburton labs introduces matrix sensors,renew power systems, inc . (rpsi), and sungreenh2 as the newest participants in its clean energy accelerator. read more https://bit.ly/3ivfncc	we are excited to announce the selected tech startups for urbantech 2021: this year, arkitema and cowi will be working with cogo, excess materials exchange , parametric solutions, treble technologies and woodsense. together, we are going to develop new, innovative solutions for more sustainable and liveable cities. (...)	the future of plastics is bio! this is the vision of biovox gmbh, one of the start-ups in this year's heraeus accelerator program. the team met atthe technische universität darmstadt and launched their company in 2020 to develop bioplasticsthat are naturally renewable, fully degradable and recyclable.

Joint Ventures	Legal creating of a new entity where two or more organizations pool their resources and share equity.	we're pleased to provide an update on our proposed joint venture with mitsui & co., ltd.we've initiated a front-end engineering and design (feed) study for the potential blue ammonia facility and have signed an agreement with thyssenkrupp. (...)	the german town of ulm has been chosen as the establishment of the new manufacturing facility of the nikola tre electric heavy-duty trucks, as partof the joint-venture between iveco and nikola motor company .	we are thrilled to announce the term sheet agreement with nobian today for the proposed formation of a 50/50 joint venture
Mergers and Acquisitions	Consolidation of organizations through one organization acquiring the other or through a joint merger of both organizations into a new organization.	voith group acquires the remaining stake in elin motoren gmbh - a voith company- a voith company. with this step we continue to strengthen our core business and consistently expand it in the direction of sustainable technologies. welcome to the voith group.	today, we announce intent to acquire german compressor manufacturer bock gmbh to strengthen expertise in energyefficientsustainable cooling. (...)	cummins inc .has bought the 19% stake it did not already hold in canadian fuel cell and electrolyser maker hydrogenics from french industrial gases companyair liquide. hydrogen cleanenergy
Certification and Approvals	Third-party assessments and approvals, such as safety certifications, environmental permits, and technical standards.	Classification society DNV has awarded an approval in principle (AiP) to South Korean shipbuilder HD Korea Shipbuilding & Offshore Engineering Co., Ltd. (HD KSOE) for its electric propulsion liquefied hydrogen (LH2) carrier design concept that could enable 80,000 cubic meters of LH2 storage and transport. & gasfor sponsoring the trip!	Sieć Badawcza Łukasiewicz – Przemysłowy Instytut Motoryzacji (PIMOT) from Poland has joined the list with certification bodies approved by the SURE-system, so that now economic operators can choose it for their system audit.(...)	ctheu.s. nuclear regulatory commission recently issued a draft safety evaluation report indicating initial nrc staff approval of the source term methodology detailed in a topical report kairos power submitted in june 2020. if approved, the final safety evaluation report will be issued early next year to utilize throughout the licensing process."this accomplishment strengthens our team's extensive pre-application engagement with the nrc and builds licensing certainty for our advanced reactor technology," (...)
Training	Educational or vocational training efforts to build capacity for deployment, maintenance, or innovation of technologies.	Congratulations to Mr.DEVANG JOSHIandRUDRA SOLAR ENERGY,CLEANMember!Under the Entrepreneurship Development Programme (EDP), launched by Modern Energy Cooking Services (MECS) and supported by the Office of the Principal Scientific Adviser (...)	Hillary Korir, Senior Economist, National Treasury & Economic Planning is facilitating a trainingon carbonmarkets for Makueni County. The training has attracted over 30 participants representing various departments in the county such as water and sanitation, lands and environment, finance, gender, agriculture, and livestock and infrastructure. (...)	delphi has teamed up with everrati automotive, a specialist in electrifying classic cars, to launch a new training program focused on electric vehicle conversions.

Table S18: **Types of climate technologies.** Note that each post can be assigned to multiple technologies.

Technology	Description	Exemplary posts		
Solar	All types of solar photovoltaic (PV) applications from small residential roof-top systes to utility-scale applications.	we are very excited to announce our investment in pvmodule coating pioneer phytonics, alongside high-tech gründerfonds,karlsruher institut für technologie (kit)/ kit-gründerschmiedeand business angles. phytonics ' novel coating enables up to 10 % higher annual electrical energy yields through higher efficiency in capturing and converting sunlight, while at the same time making the modulesglare-free. (...)	announcement: we today bring you news of our partnership with aberdeen city council on a smart social housing project, supported by the uk government's social housing decarbonisation fund (shdf) demonstrator. utilising sms's newly launched solopower(a financed solar pv and battery storage solution), the project will additionally trial the electrification of heat and fabric upgrades as part of a whole-home approach to reducing co2 and fuelpovertyacross an initial 100 homes.	our strong cooperation with fortis energy continues. we have supplied over 100 mw panels to fortis enerji, which we have provided over 100 mw of panels so far, and this time, we have shipped 2,432 panels for the 1,097 kwp ges project in uzundere. thank you
Electric Vehicles	All non-hybrid types of battery electric vehicles, such as electric cars, buses, and trucks. Corresponding collaborations can also refer to the necessary infrastructure (e.g., charging stations) and related business models (e.g., shared e-mobility).	enertech capital is pleased to announce today, our first investment from the enertech global strategic mobility fund in leading electric vehicle ("ev") battery intelligence company recurrent."we are pleased to have enertech join the syndicate of investors in our latest round." (...)	congratulations to arcus asset company horizon energy infrastructure on their new partnership with good energy, creating support for uk business customers looking to install ev charging infrastructure!	vdl nedcar has been instructed to take the very first models of the mini cabrio electric into production. the mini cooper se convertible is the world's first convertible with a 100% electric powertrain. the production of the model is limited to 999 pieces and starts in april 2023.
Green Hydrogen	All technologies related to the production, transport, storage, and usage of green hydrogen across different sectors.	totalenergies has opened a public hydrogen station on the territory of vdl in veldhoven. "vdl groep plays a prominent role in the field of sustainable energy, for both stationary and mobile applications."said pieter van der leegte. (...)	alstom in partnership with the government of quebec, chemin de fer charlevoix, train de charlevoix , harnois énergiesand htechas announced a passenger service demonstration project for its coradia ilint hydrogen-powered train.	we've signed a collaboration agreement with liebherr group in order to optimise hydrogen fuel cells alstom's hydrogen strategy is part of its ambition to innovate by pioneering smarter and greener mobility solutions for all. this agreement is aimed at optimising hydrogen systems, including improving the reliability and durability of fuel cells, increasing their power density and reducing the cost of such solutions.
Wind (Onshore)	Onshore wind turbines as well as the manufacturing of parts (e.g., turbine blades).	we are excited to announce that we've entered into a power purchase agreement with Orsted, supporting the construction of the sunflower wind project, which will match 100% of our power consumption across our entire operational footprint with renewable energy credits.(...)	Our supported company act blade continues to inspire us with its winds of change! after a six-month test in scotland, they explain how their greener, leaner high-tech textile rotor blade s fly through trials in the uk's biggest onshore wind farm. (...)	aerones , supported by eit innoenergy, is revolutionising the maintenance of wind turbines. recent data from inspections carried out by the latvian company, on more than 1,500 blades in different environmental conditions across the world, show that approximately 23% of the blades have broken or damaged spcrs.

Batteries	All types of battery applications for energy storage, including mobility and grid storage applications.	we are pleased to announce that the im3ny new york lithium ion battery plant is now 51% complete see our latest asxannouncement https://lnkd.in/gb_vhxir	the finnish cleantech company tracegrow offers a sustainable solution for recycling valuable materials back into circulation. its technology converts industrial side streams and recycled batteries into valuable products for agriculture and other industries without the need for energy-intense mining operations and reducing its environmental impact. nefco - the nordic green bank's fast-track loan will help tracegrow implement its new growth strategy and allow it to hire additional personnel to strengthen its global reach.	kore power has acquired a 4.22% stake in zevx inc., an innovative phoenix, az area startup focusing fleet electrification and ev conversion kits. this investment expands the company's presence in the e-mobility space after entering into a supply agreement to provide kore battery modules for zevx 's electric powertrain kits through 2030. read more: https://lnkd.in/ggbjshdx
Biogas	Production, transport,storage, and usage of renewable gases based on raw materials, such as agricultiral waste, municipal waste, and plant material.	eit - european institute of innovation and technology innoenergy supported the start-up orchestra which produces economically viable technology for biogas upgrading using selective co2 separation for removal and purification.	a territorial methanisation site in haute-savoie, france, was inaugurated yesterday. for the first time ever, @ ifp energies nouvelles and @ arol energy demonstrated a new biogas purification technology called ae-amine.it will use treated biogas to produce 110 nm3/h of biomethane providing 8000 mwh of energy each year, equal to the annual heating needs of 1 200 people!	we are turning organic waste into renewable natural gas with our partners stormfisher. learn how we're creating rngto heat homes and more at https://lnkd.in/e_43kisc.
Carbon Capture and Storage	All applications capturing CO_2 directly from a point source (e.g., an energy plant). For Bioenergy with Carbon Capture and Storage (BECCS) applications both CCS and the bioenergy source are classified as relevant.	pilot energy limited, and canadian carbon capture & removal solutions providers vante have signed a memorandum of understanding (mou) to collaborate on offering a one-stop-shop solution for carbon capture, transportation, and storage to industrial businesses with hard-to-avoid co2 emissions. pilot energy and svante will initially target the decarbonisation of $\sim$8-million tonnes per annum of co2 emissions from western australia's kwinana industrial area. find out more:bit.ly/3gwazl8	kudos to the translational energy research centre on advancing carboncapturetechnology. we're excited to collaborate with them to expand options for zero carbon solutions.	we're excited to see the carbon capture unit being built at landmark power holdings and victory hill capital partners llp's site in rhodesia. one step closer to cleaner, more flexible power generation!
Biofuels	Production, transport,storage, and usage of renewable fuels from biomass.	c-green's full-scale oxypower htc plant for converting industrial biosludge to renewable biofuel is now under construction. the facility will recycle 16,000 metric tons of pulp biosludge a year at stora enso's fluting paper mill in heinola, finland. the goal is to reduce annual carbon dioxide emissions by as much as 2,500 tons. http://bit.ly/2miufca	we are proud to provide families & businesses with an affordable and reliable energy choice while advancing innovative low-carbon solutions like green fuels. we are excited to partner with municipality of chatham-kentand waste connections of canada to advance these important projects!	congratulations to pkn orlen s.a. andorlen poudnie s.a. for kicking off the execution of their second-generation cellulos ethanol plant in poland. we look forward to our cooperation to make the plant producing biofuels with our sunliquidtechnology a great success.
Hydro Energy	All types of hydropower plants including conventional dams and pumped storage.	tractebel and partner norconsult as celebrated the successful completion of the 456 mw upper tamakoshi hydroelectric project on september 27 at heritage garden, lalitpur, nepal.	the construction of the expansion of the downstream batard began on the hydroelectric development project of the nachtigal dam, in cameroon	new lai chau hydropower plant completed one year early! ge renewable energy and its consortium partner powerchina zhongnan engineering corporation recently received the final acceptance certificate from vietnam electricity (evn) for the new laichauhydropower plant. this great milestone marks the full and successful completion of the plant, one year ahead of schedule.

Sustainable Aviation Fuels	All types of sustainable aviations fuels including biofuel-based aviation fuels and hydrogen-based aviation fuels.	neste my sustainable aviation fuel is introduced for the first time at gatwick airport through a collaboration between neste, q8aviation, easyjet and gatwick airport ltd.this important milestone marks the first time a departing flight at gatwick has used sustainable aviation fuel (saf) and isalso the first usage by any easyjet service.	aer lingus enters into new fuel sales agreement with gevo for 6.3 million gallons of sustainable aviation fuel per year over five years.	breakthrough energy catalyst grantee lanzajet is building a groundbreaking facility that is expected to produce 9m gallons of sustainable aviation fuel annually. the facility will help accelerate the global transition away from high-emission jet fuels. more: https://nt-z.ro/3ixhczc
Nuclear Fission	All processes related to energy generation from nuclear fission including nuclear material production and waste treatment as well as mall-scale and large-scale reactors.	icymi: our partners deep isolation launched the new deep borehole demonstration center at wmsym2023 for nuclear waste in phoenix, arizona!	we are excited to announce that we have signed a contract with dominion energy to design, manufacture and deliver six replacement steam generators at surry nuclear power station in virginia. the new deal reinforces our long-term partnership with dominion to help support surry's operations through 2053.the nuclearenergyproduced by the power station provides carbonfreeelectricity year-round to 419,000 homes.	how to integrate small modular reactors into low-carbon hybrid energy systems. tractebel leads the industrial users group (iug) of tandem project, a euratom supply agency horizon europe research project, that aims at facilitating the safe & efficient integration of smrs into smart low-carbon hybrid energy systems. learn more: https://tandemproject.eu/
Heat Pumps	All applications of heat pumps including production, installation, and operation.	we are thrilled to announce endurant energy's acquisition of geoptimize inc., a specialist in heating and cooling and ground source heat pump gshp design company.	planning has been submitted for a renewable-led energy centre with water source heat pump technology to help power the mersey heat district heat network at peel liverpool waters. we're pleased to be working withpeel l&pas the project enters this exciting phase.	the first heat pump installations of our customer quattzijn are now successfully implemented. the commander in chief is a good result of our intensive cooperation. in the coming period, production will be increased so that more houses can be provided with this beautiful product.
Biomass	All solid types plant-based biomass for energy generation, such as charcoal and pellets.	each year, the new facility will produce 10,000 tonnes of biocarbon as a coal fuel alternative for ontario's heavy industries. the biocarbon is expected to provide enough gas in thorold for 5,500 ontario homes. natural gas must be part of a low-carbon energy future. wastetoenergyinitiatives such as char technologies ltd. biomass to rng facility will improve agricultural and landfill environmental conditions, produce rng and biocarbon, reduce emissions, and advance ontario's sustainability and energysecurity	a team of foley lawyers recently acted as legal counsel to greenleaf power consolidated llc (greenleaf) in securing $36.7 million in project financing from east west bank through its wholly-owned subsidiary greenleaf biomass holdings llc. the transaction marks one of the largest biomass power project financings in recent north american history.	greenwood sustainable infrastructure, our north american sustainable infrastructure investment company, has announced that its michigan-based clean power business, warden electric company, is undertaking a major upgrade at its flagship biomass power plant that will include refurbishment of its ge turbine, as well as a number of improvements to the boiler and related systems. this is the first phase of a refurbishment programme expected to exceed $6 million in capital expenditure. (...)
Marine Energy	All types of applications to generate electricity from ocean waves, tides, and temperature differences.	a tidal-powered airport might not be far off! the team atemec: european marine energy centre is working through the logistics of turning o2's tidal power into green hydrogen, that can then be used for carbon-free local air services here in orkney.	corpower ocean launches pioneering wave energy project in northern portugal.with a 16 meur investment plan, corpower ocean is establishing an r&d, manufacturing & service centre for wave energy converters in viana do castelo.“ corpower's goal is to successfully introduce certified and warrantied wec products to the market by 2024	swedish marine energy developer minesto has secured a power purchase agreement that will support a prospective tidal energy project in the faroe islands. minesto signed a ppa with the faroese electric utility company elfelag sev - electrical companyfor two planned 100kw systems, featuring the swedish company's subsea kite technology, and an additional 2 mw of capacity for large-scale tidal energy systems.

Geothermal Energy	All types of applications to extract heat from the earth's crust.	eavor is proud to sign an agreement with getechto explore geothermal opportunities across latin america! read the full blog here - https://lnkd.in/gxvfvnge eavor energy #geothermal #renewable #energyforeavor #geothermalenergy	we are thrilled to announce the close of our series b round of funding led by breakthrough energy ventures, along with continued support fromgv, comcast ventures, new enterprise associates (nea), collaborative fund, lennar, and building ventures. this new investment enables us to expand operations, deepen our research & development and bring sustainable geothermal heating to the millions of homes that need it.here's to the decarbonized future ! https://lnkd.in/dz78qay #geothermalenergy	wien energie gmbh and omv join forces to develop deep geothermalenergy in the vienna region. joint venture planned for the design and development of geothermal potential in the vienna basin as well as for the operational management of deep geothermal plants.
E-Fuels	All types of electric fuels based on hydrogen.	hy24 , mirova , cdpq and technip energies are joining forces to invest €200m in hy2gen ag, a pioneer in the production of green e-fuels for mobility, agriculture and industry.societe generale acted as financialadvisorto hy24 and mirova on this project, the largest private green hydrogen-focused capital raise to date and paving the way for the decarbonizationof industrial and transportation sectors.	sasol chemicals provides the clean tech company ineratec with catalyst for the fischer-tropsch reactors. the plant at industriepark hoechst will produce up to 2 500 tons of synthetic fuels with power-to-liquid technology.read more https://lnkd.in/dw6qktzd	next milestone for power to liquids production at the hamburg h&r location. p2x europe gmbh & co kg, the joint venture between h&r group and mabanaft, is gaining momentum: the production and marketing of synthesis-based efuels and waxes from renewable raw materials at the hamburg site is set to start soon. with the innovative demonstration plant by technology partner ineratec gmbh around 200 metric tons of e-fuels per year for mobility, and around 150 metric tons of waxes for applications in the cosmetics, pharmaceuticals and food industries will be produced. https://lnkd.in/ewefbemf
Nuclear Fusion	All types of applications generating energy from nuclear fusion.	we're thrilled to announce that we're collaborating with experts at canadian nuclear laboratories to advance commercial fusion power in canada. learn more: http://bit.ly/3udr8vu	the ga energy group is excited to announce a new collaboration with tokamak energyto advance high temperature superconducting magnet technology for fusion energy and other applications. this collaboration will leverage our world-leading capabilities for manufacturing large-scale magnet systems and te's pioneering expertise in hts magnet technologies.read more: https://bit.ly/42fmpi5 fusionenergy	we're building a world-first tritium research centre to develop fuel technology for fusion energy devices across the globe - and we're pleased to announce that atkins will be designing it
Direct Air Capture	All processing steps related to capturing CO_2 from the atmosphere via direct air capture.	oxy and our subsidiary 1pointfive to begin construction of the world's largest direct air capture plant in the tx permian basin, advancing large-scale carboncaptureto help oxy and others reduce emissions and accelerate the path to netzero. learn more: https://bit.ly/3wtb5ue	we're pleased to announce that our new large-scale direct air capture plant "orca" has successfully achieved independent third-party validation from dnv, the global leader in quality and risk assurance. (...)	we're pleased to share that the u.s. department of energy (doe) officially selected fervo's red rocks direct air capture hub in southwest utah for $2.9 million in federal funding.
Biochar	Production and use of biochar based on pyrolysis to extract CO_2 from the atmosphere.	partnership announcement: we are happy to announce our new partnership with vanmander, the first company to trade biochar-based carbon removal credits in spain and portugal, and our first spanish supply partner!	the biggest and most technologically advanced purpose built biochar manufacturing facility in the us takes shape. our two pyreg gmbh p-1500 machines were delivered last week and supporting infrastructure is on the way. this project has been made possible with financing fromcei (coastal enterprises, inc.), finance authority of maine, maine technology institute, grants from the u.s. forest service.	aston university is to receive £1.8 million to transform the west midlands into a powerhouse of low-carbon product development and commercialisation.the university will be building on its existing research facilities to lead the region's biochar cleantech accelerator as part of the west midlands innovation accelerator.

Offshore Wind	Wind energy generated by turbines located offshore, typically in bodies of water. Includes innovation activities related to parts (e.g., foundation, floating platform).	It's been a busy few weeks for our #FloatingOffshoreWind programme. The Crown Estate exists to create value both now and for future generations, and our proposals for floating wind off the coast of South West England and South Wales are part of our role in catalysing the UK's transition to Net Zero while ensuring we support a thriving marine environment and create new social and economic opportunities (...)	OW Ocean Winds has been granted a feasibility license by the Australian Government to develop an #offshorewind farm in waters off Gippsland, Victoria. Learn more:https://bit.ly/4b1rBJr	ørstedhas signed an agreement with funds managed by schroders greencoat llpto divest its remaining 25% minority interest in the 630mw london array offshore wind farm in the uk. offshorewind uk deals
Concentrated Solar	Solar energy technologies using mirrors or lenses to concentrate sunlight onto a small area to generate heat or electricity, including CSP and solar towers.	[sustainablefinance] masdar (abu dhabi future energy company), a leader in renewable energy & sustainable urban development has issued the 1st green tradefinanceline in the middle east. this will help finance wind power, photovoltaic power and concentrated solar power projects in the region. thefutureisyou https://lnkd.in/dekbqhz	Sodium-ion battery maker Natron in talks for Australia hybrid 50MW CSP and PVplant: ast Solar Pty Ltd's modular tower CSP technology linked to a 56MW steam turbine via a 14.5 hour molten salt#thermalstorage system 80MW PV with single axis tracking An integrated 52MW / 15MWh battery energy storage syste 57MW of gas-powered reciprocating engineshttps://lnkd.in/dgTS3W8Y#solar#thermal#concentrated	European Investment Bank ponders support for #CSP plus storage project in Greecehttps://goo.gl/GPAVri #solar #thermal #concentrated Nur Energie
Waste to Heat	Technologies that convert waste materials into usable heat, often via incineration or pyrolysis. Includes industrial and municipal applications.	a wastetoenergyplant will be constructed in aberdeen, scotland. the plant will utilize 150,000 tons of wasteper annum with a total output of 49 mwth. the electricitywill fed into the national grid and the steamwill be used in the local district heat network. standardkessel baumgarte gmbhacciona	[power] pride and success for maximum sustainability! we are proud to have had the contract for the complete overhaul and rotor rewinding of the lsa 56 bxl95 alternator driven by a steam turbine at the cogeneration plant in the swedish town of västervik. the plant uses household waste as fuel, where the energy is recovered through hot water to supply the district heating system of the municipality, and the steam drives a turbine that powers our generator. (...)	this morning we're very pleased to announced the planned acquisition & recommissioning of a 1mwe wastetoenergyplant in italy. we're working with metalnrg plc and two other partners to repower, own and operate, the biomass-to-energy plant, with eqtec advanced gasification technology, to transform straw and forestry wood waste from local farms and forests into green electricity and heat for use in the local community. (...)
Bioenergy with Carbon Capture and Storage (BECCS)	BECCS involves capturing and storing CO2 emissions from biomass-based energy production processes.	One of Europe's first large-scale plants for carbon dioxide capture, will be built by Stockholm Exergi and it will be built in Stockholm, in Värtahamnen. This presentation asked for a permit to build a large-scale facility, which could be used for capturing biogenic carbon dioxide. (...)	The UK government is poised to approve the multi-billion BECCS scheme of energy major Drax Group that involves attaching two carbon capture plants to the group's four generating units in North Yorkshire, The Telegraph has reported. #carboncapture #BECCS #CO2storage #climatepolicy	we are advancing our plans to deliver beccs at drax. the announcement follows news that the east coast cluster, a collaboration between zero carbon humber , net zero teesside , and the northern endurance partnership, which plans to create the uk's first net zeroindustrial cluster, has received government backing. we are an anchor project in the east coast cluster and the commencement of its planning consultation marks the first major action from a project in the cluster. find out more. https://lnkd.in/d6yqis-b
Carbon Direct Removal (Other solutions)	Technologies and natural solutions aimed at removing CO2 directly from the atmosphere that are not included in the set of climate technologies (e.g., afforestation, enhanced weathering).	Captura, a $1 million Xprize winner in 2022, announced on January 22nd it has raised $21.5 million in an expanded Series A funding round to commercialize its ocean carbon removal technology. #carbonremoval #CO2removal #climatetech #climatefinance https://bit.ly/3SsRPO3	partner showcase:nextgen cdr facilitynextgen, a collaboration drawing on the expertise of south poleand mitsubishi corporation , is the first truly global facility of its kind, bringing together leading multi-national buyers from across asia, europe, and north america to promote the market for high quality, certified carbon removals (cdrs) from technological projects. (...)	pleased to share our first climatetechinvestment - fairatmos !fairatmos is all about democratising access to carbon markets.the indonesia-based carbon technology platform, has just announced their raise of us$4.5 million in its seed round, led by go-ventures and kreasi terbarukan tbs, the investment arm of one of indonesia's leading integrated energy companies, toba bara sejahtera.we, vertex ventures southeast asia and india and other prominent angel investors also participated. congrats tonatalia rialucky marsudiand team! (...)

Railway	Technologies and systems related to electric or hydrogen-powered rail transport and supporting infrastructure.	Helsinki light rail line begins operations ahead of schedule. Helsinki light rail line 15 is designed to provide a new, zero-emission mode of travel that will improve crosstown transport services and connectivity.Helsingin kaupunki – Helsingfors stad – City of HelsinkiEspoon kaupunki - Esbo stad - City of Espoo	IN THE NEWS: The project team atCaltrainis celebrating a major milestone – electrification of the second Traction Power Substation in South San Francisco! This latest accomplishment signifies major progress in expanding Caltrain's ability to test and run electric trains along the corridor. Learn more:https://bit.ly/3R9yHEy#Caltrain#rail#BuildtoLast	čd - telematika has chosen alstom to equip seven pendolino trains and 66 electric vehicles with etcs level 2.read more here: https ://lnkd.in/eaeevix rail transport alstom cdtelematika rollingstock electrictrains railwaysignalling etcs
Electric Shipping	Marine vessels powered fully or partially by electric propulsion systems, including battery electric and hybrid systems.	Congratulations toSandith Thandasherryand-NavAlt Solar & Electric Boats Pvt Ltdfor winning Gussies Electric Boat Award for 'Excellence in Electric Boats Designed for Paying Passengers'.PlugboatsNavAlt Solar and Electric BoatsThe Aditya - India's first commercially viable mode of transport powered by solar energy was manufactured for Kerala State Water Transportation Department and launched on 12th January 2017. (...)	Spain bankrollsAPM Terminals-Barcelona's electrification pilot project#financing#maritime#ports#decarbonization#shipping#electrification#spain	excitingnews: kreisel electric secures €50 million battery deal with swedish electric boat company#electrification#electric boats.the partnership will see x shore's flagship model, the eelex 8000, and its 225 kw motor, being exclusively powered by two state-of-the-art kreisel battery packs (kbp 63) with a total battery capacity of 126 kwh. https://lnkd.in/dmn5esyt gogreen electricboats sustainability performance cooperation marine marineindustry boating battery batterytechnology
Electric Aviation	Aircraft using electric propulsion, either from batteries or hybrid-electric systems. Includes charging and air traffic integration.	Design of a Power-Dense Aviation Motor with a Low-Loss Superconducting Slotted Armature byNorwegian University of Science and Technology (NTNU)'s team includingRunar Mellerud,Casper Klop,Christian Hartmannand-Jonas Kristiansen Nøland(...)	elec tra.aeroinc. is awarded a phase iii contract through the united states air force afwerx agility prime program!with a previous sbir d2p2 contract also under their belt for the development of their hybrid-electric propulsion system technology, this piii will accelerate electra's plan to begin flight testing a full-scale hybrid estol technology demonstrator aircraft later this year. https://lnkd.in/dppzrrsc sbir d2p2 phaseiii award contract estol hybrid electric sustainable technology aircraft aviation agilityprime afwerx	icymia university of strathclyde researcher has been awarded a prestigious european research council starting grant for a five-year project to electrify aircraft using a novel superconducting machine technology.professor min zhang, from the applied superconductivity laboratory, will focus on three ground-breaking technologies to enable the use of high temperature superconductors for electrical propulsion motors with high performance and reliability.critical temperaturea superconductor is a substance which offers no resistance to the electric current when it becomes colder than a critical temperatureby the end of the "superconducting electrical machines for zero emission aviation" (...)
Fuel Cell Aviation	Aviation technologies powered by hydrogen fuel cells, including aircraft design, onboard systems, and refueling infrastructure.	a great day meeting with the jetzero zero emissions flight delivery group at cranfield, discussing our four-phase strategy for developing zero-emissions aircraft, starting with our work on converting a conventional britten-norman islander to hydrogen-propulsion.(...)	rolls-royce has announced a significant milestone in its pursuit of future carbon-free aviation by successfully running a modified version of a standard jet engine at takeoff power using hydrogen (...)	We've got mad props! FIt check of our propeller to our hydrogen electric aircraft#Protium.#sustainableaviation#hydrogeneconomy#hydr of LancasterAgility PrimeU.S. Small Business AdministrationCalTestBedCalifornia Energy Commission

Table S19: Percentage of national partnerships in technology innovation networks for the periods Pre-IRA (01.2020–06.2022), Post-IRA (07.2022–12.2024), and as a comparison between the two periods. HQ: Percentage of partnerships between organizations with headquarters in the same country. Any: Percentage of partnerships between organizations with any location in the same country. Climate technologies are ordered by their increase in partnerships with headquarters in the same country (HQ Δ).

Climate Technology	**Pre-IRA**		**Post-IRA**		**Comparison**	
	HQ	**Any**	**HQ**	**Any**	**HQ Δ**	**Any Δ**
Nuclear Fusion	0.37	0.44	0.51	0.54	0.14	0.09
Direct Air Capture	0.44	0.47	0.52	0.57	0.08	0.11
E-Fuels	0.41	0.52	0.47	0.56	0.07	0.03
Waste to Heat	0.53	0.59	0.59	0.64	0.06	0.04
Electric Aviation	0.45	0.55	0.49	0.57	0.04	0.02
Sustainable Aviation Fuels	0.41	0.51	0.45	0.55	0.03	0.04
Marine Energy	0.44	0.51	0.47	0.53	0.03	0.01
Concentrated Solar	0.28	0.36	0.29	0.34	0.01	-0.02
Hydro Energy	0.34	0.40	0.34	0.42	0.01	0.02
Electric Vehicles	0.59	0.68	0.59	0.66	0.00	-0.02
Hydrogen	0.51	0.59	0.51	0.57	0.00	-0.02
Geothermal	0.58	0.62	0.58	0.64	0.00	0.01
Carbon Capture And Storage	0.47	0.57	0.46	0.56	-0.01	-0.02
Wind (Onshore)	0.45	0.56	0.43	0.52	-0.02	-0.04
Biofuels	0.47	0.55	0.45	0.52	-0.03	-0.03
Offshore Wind	0.44	0.56	0.41	0.51	-0.03	-0.05
Biomass	0.51	0.55	0.47	0.52	-0.04	-0.04
Solar	0.52	0.62	0.48	0.56	-0.04	-0.06
Biogas	0.64	0.70	0.59	0.64	-0.05	-0.06
Nuclear Energy	0.65	0.72	0.60	0.66	-0.05	-0.06
Battery	0.51	0.60	0.46	0.53	-0.05	-0.07
Bioenergy with Carbon Capture and Storage	0.60	0.67	0.55	0.59	-0.06	-0.07
Heat Pumps	0.69	0.72	0.63	0.66	-0.06	-0.05
Fuel Cell Aviation	0.57	0.65	0.49	0.58	-0.07	-0.07
Carbon Direct Removal	0.48	0.61	0.39	0.48	-0.09	-0.13
Electric Shipping	0.50	0.58	0.39	0.45	-0.10	-0.14
Biochar	0.61	0.69	0.49	0.55	-0.12	-0.14
Railway	0.45	0.53	0.30	0.36	-0.15	-0.17
All	0.51	0.60	0.49	0.57	-0.02	-0.03

Table S20: Countries with the highest increases in centrality of governmental organizations and of all domestic organizations between the periods 01/2020–06/2022 and 07/2022–12/2024. Centrality increases for governmental organizations are measured as the difference in accumulated degree centrality between the two periods–that is, the number of additional links to governmental organizations in the network. Centrality increases for all domestic organizations are calculated analogously, considering all organizations headquartered in the country. Technologies where the country with the largest increases in governmental centrality also marks the country with the largest overall increase in centrality of domestic organizations are highlighted in gray. The *Multiplier* column reports, for the country with the highest increase in governmental centrality for each technology, the ratio of the absolute increase in centrality by all domestic organizations to the increase by governmental organizations. This reflects the extent to which broader domestic centrality expanded relative to government involvement.

Climate Technology	**Country with Highest Increase in Centrality of Governmental Organizations**	**Country with Highest Increase in Centrality of All Domestic Organizations**	**Multiplier**
Battery	US	US	8.53
Bioenergy with Carbon Capture and Storage	SE	GB	5.99
Biochar	US	US	10.28
Biofuels	FR	GB	6.37
Biogas	FR	FR	4.69
Biomass	FR	FR	4.73
Carbon Capture And Storage	DK	GB	4.27
Carbon Direct Removal	US	US	13.79
Concentrated Solar	DE	ES	4.05
Direct Air Capture	US	US	7.03
E Fuels	DE	DE	8.43
Electric Aviation	US	US	5.29
Electric Shipping	NO	NO	5.70
Electric Vehicles	US	US	5.82
Fuel Cell Aviation	FR	FR	8.20
Geothermal	FR	US	3.57
Heat Pumps	GB	GB	4.64
Hydro Energy	FR	FR	7.03
Hydrogen	FR	FR	5.84
Marine Energy	GB	GB	8.14
Nuclear Energy	US	US	3.15
Nuclear Fusion	US	GB	3.24
Offshore Wind	GB	GB	7.22
Railway	FR	ES	5.65
Solar	FR	FR	6.01
Sustainable Aviation Fuels	GB	US	9.37
Waste to Heat	FR	FR	5.42
Wind	FR	GB	7.60

Table S21: Performance of the sector classifier on test data, using randomly sampled and manually labeled text descriptions of organizations.

Sector	Precision	Recall	F1-score	True Positives
Climate technology sub-sectors				
Battery	0.88	1.00	0.93	7
Biofuels	0.91	1.00	0.95	10
Biogas	0.86	1.00	0.92	6
Biomass	1.00	1.00	1.00	10
Carbon Capture And Storage	1.00	1.00	1.00	4
Carbon Offsets	1.00	1.00	1.00	4
Direct Air Capture	1.00	1.00	1.00	5
Electric Vehicles	0.78	0.88	0.82	8
E-Fuels	1.00	0.80	0.89	5
Geothermal	1.00	1.00	1.00	4
Heat Pumps	1.00	1.00	1.00	5
Hydrogen	1.00	1.00	1.00	10
Hydro energy	1.00	1.00	1.00	6
Marine Energy	0.80	1.00	0.89	4
Nuclear Fission	1.00	1.00	1.00	8
Nuclear Fusion	0.83	1.00	0.91	5
Other Carbon Removal	0.88	1.00	0.93	7
Other Energy Storage	0.83	0.83	0.83	6
Solar	1.00	0.93	0.96	14
Sustainable Aviation Fuels	1.00	1.00	1.00	4
Wind	1.00	0.92	0.96	13
Other Renewables	1.00	1.00	1.00	1
Fossil energy sub-sectors				
Coal	1.00	1.00	1.00	4
Gas	1.00	0.80	0.89	15
Oil	1.00	1.00	1.00	9
Other Fossil Energy	1.00	0.50	0.67	4
Other energy-related sub-sectors				
Electricity Grid	1.00	0.80	0.89	5
Energy General	0.94	0.94	0.94	18
Transport sub-sectors				
Automotive	0.86	1.00	0.92	6
Aviation	1.00	0.90	0.95	10
Railway	0.75	1.00	0.86	3
Shipping	0.83	1.00	0.91	5
Other Transport	1.00	0.83	0.91	6
Other relevant sectors				
Built Environment	1.00	1.00	1.00	14
Chemical Industry	0.92	1.00	0.96	11
Computer and Electronic Products	1.00	0.67	0.80	9
Iron and Steel	1.00	0.86	0.92	7
Military	1.00	0.75	0.86	4
Other Construction	1.00	0.86	0.92	14
Other Manufacturing	0.92	1.00	0.96	11
Raw Materials	1.00	1.00	1.00	6
Software	1.00	0.75	0.86	12
Other ICT	1.00	0.92	0.96	13
Sector classifier (avg.)	0.95	0.93	0.93	332

Table S22: Performance of the organization type classifier on test data, using randomly sampled and manually labeled text descriptions of organizations.

Organization type	**Precision**	**Recall**	**F1-score**	**True Positives**
Accelerator/Incubator	1.00	1.00	1.00	4
Bank	1.00	1.00	1.00	4
Consulting	1.00	1.00	1.00	8
Event Organizer	1.00	0.60	0.75	5
Governmental Organization	1.00	0.93	0.97	15
International Organization	0.75	1.00	0.86	3
Lobby Group	1.00	1.00	1.00	5
Manufacturer	1.00	1.00	1.00	9
Media Firm	0.80	1.00	0.89	4
Mining	1.00	1.00	1.00	4
Non-Governmental Organization (NGO)	0.82	1.00	0.90	9
Other Financing Organization	1.00	0.94	0.97	16
Project Developer	1.00	1.00	1.00	5
Research Institute	0.86	1.00	0.92	6
Service Provider	1.00	0.87	0.93	15
University	1.00	1.00	1.00	3
Utility	0.83	1.00	0.91	5
Venture Capital	1.00	1.00	1.00	6
Organization type classifier (avg.)	0.95	0.95	0.95	126

Table S23: Prompt used for the sector classifier for organizations.

You are a research assistant classifying organization profiles on LinkedIn. Classify the organization into one or multiple of the following sectors:
"Biomass": "Organic material used for energy production", "Biofuels": "Liquid fuels from biological sources", "Biogas": "Gas from anaerobic digestion of organic matter", "Wind": "Energy from wind turbines", "Solar": "Photovoltaic or solar thermal energy", "Direct Air Capture": "Technology that removes CO2 directly from air", "Carbon Capture And Storage": "Capturing and storing CO2 emissions", "Other Carbon Removal": "Non-DAC, non-CCS carbon removal methods", "Carbon Offsets": "Credits to compensate for CO2 emissions", "Hydrogen": "Hydrogen production and utilization for energy", "Nuclear Energy": "Conventional nuclear fission energy", "Nuclear Fusion": "Energy from fusion of atomic nuclei", "Hydro energy": "Hydro power and hydro pumped storage", "Geothermal": "Energy from Earth's internal heat", "Battery": "Electrochemical energy storage systems", "Other Energy Storage": "Non-battery energy storage (e.g., thermal)", "Electricity-grid": "Power transmission and distribution infrastructure", "Electric Vehicles": "Battery-powered vehicles", "Sustainable Aviation Fuels": "Low-emission fuels for aircraft", "E-Fuels": "Synthetic fuels from renewable electricity", "Marine Energy": "Electricity from tidal or wave motion", "Heat Pumps": "Devices for efficient heating and cooling", "Other Renewables": "Renewable energy not otherwise listed", "Gas": "Natural gas production or use", "Oil": "Petroleum extraction, refining or distribution", "Coal": "Coal mining and combustion", "Other Fossil Energy": "Fossil-based energy not in gas/oil/coal", "Energy General": "Broad or mixed energy sector activity", "Railway": "Rail transport systems and services", "Aviation": "Air transport and related infrastructure", "Shipping": "Maritime transport of goods or people", "Automotive": "Design or production of motor vehicles", "Other Transport": "Transport modes not elsewhere specified", "Chemical Industry": "Production of chemicals and related products", "Built Environment": "Buildign constrction and operations", "Other Construction": "Construction not focused on buildings", "Computer and Electronic Products": "Hardware and electronic devices", "Software": "Development of software products or services", "Other ICT": "IT and communications not covered above (e.g., cloud systems)", "Agriculture": "Farming, crop, and livestock production", "Iron and Steel": "Production of iron and steel materials", "Other Manufacturing": "Manufacturing not in listed sectors", "Military": "Defense and military-related activities", "Raw Materials": "Mining or extraction of basic materials", "Other Sectors": "Does not fit into listed sector categories"
Guidelines for Output: Use consistent formatting for responses. Only provide the classification. Do not repeat the post or add explanations. Use the label "Other Sectors" if the organization does not specify any sector (e.g. financial services in general) or the sector does not fit to any of the labels (e.g., textiles). Marine energy refers to tidal and wave electricity generation only.

Here are some exemplary classifications:
Text: Fraunhofer-Institut für Solare Energiesysteme ISE; The Fraunhofer Institute for Solar Energy Systems ISE in Freiburg, Germany is the largest solar research institute in Europe. With a staff of about 1400, we are committed to promoting a sustainable, economic, secure and socially just energy supply system based on renewable energy sources. We contribute to this through our main research areas of energy provision, energy distribution, energy storage and energy utilization. Through outstanding research results, successful industrial projects, spin-off companies and global collaborations, we are shaping the sustainable transformation of the energy system. https://www.ise.fraunhofer.de/en/publishing-notes.html; ['Photovoltaik', 'Energiesystemtechnik', 'Solarthermie', 'Gebäudeenergietechnik', 'Wasserstofftechnologien']; ['#energytransition', '#research', '#solar']
Classification: Solar
Text: Esken; We own two core assets; London Southend Airport and Stobart Energy.London Southend Airport is an award-winning airport serving London and the South East. It has ambitions plans to grow and the key ingredients in place to enable that growth. And; in Stobart Energy we have a transformational and maturing business which supplies fuel to biomass plants across the UK so that they can, in turn, create renewable energy.; ['Infrastructure and Support Services', 'Railway Maintenance', 'Biomass Energy', 'Aviation', 'Biomass'];
Classification: Aviation, Biomass, Railway
Text: LanzaTech; Where others see a dire choice, LanzaTech sees a trillion-dollar opportunity.The good news is after 15 years, north of a thousand patents, and millions of hours of pioneering scientific inquiry, LanzaTech has invented a technology big enough to meet the moment. One that transforms pollution into profit, and ensures that humans continue to prosper far into the post-pollution future.The science is state-of-the-art, but the idea is simple. We use nature to heal nature. First we capture carbon emissions. Then we feed them into bioreactors where trillions of carbon-hungry microbes go to work. These tiny dynamos eat the pollution and output valuable raw material commodities. Pure enough to be resold, repurposed, recycled, renewed, re-everythinged — from sustainable jet fuel to yoga pants.It's a commercial scale solution that's ready for market today. In a crowded sector filled with speculation but short on results, our plug-and-play platform is already making our customers money. Turns out science and business makes one helluva team.Waste carbon pollution is humanity's biggest threat. LanzaTech is turning it into an opportunity. Reducing emissions and making money for our customers — today. Let's transform our tired Lose-Lose climate debate into a Win-Win proposition. One that helps companies grow their revenue while helping the planet reach a post-pollution reality. LanzaTech — Welcome to the Post Pollution Future; ['chemical recycling', 'carbon emissions', 'air quality', 'circular economy', 'green chemistry', 'carbon recycling', 'climate action', 'fuels and chemicals']; ['#lanzatech', '#circulareconomy', '#carbonrecycling']
Classification: Other Carbon Removal, Sustainable Aviation Fuels, Chemical Industry
Text: RWE; RWE is leading the way to a green energy world. With an extensive investment and growth strategy, the company will expand its powerful, green generation capacity to 50 gigawatts internationally by 2030. RWE is investing €50 billion gross for this purpose in this decade. The portfolio is based on offshore and onshore wind, solar, hydrogen, batteries, biomass and gas. RWE Supply & Trading provides tailored energy solutions for large customers. RWE has locations in the attractive markets of Europe, North America and the Asia-Pacific region. The company is responsibly phasing out nuclear energy and coal. Government-mandated phaseout roadmaps have been defined for both of these energy sources. RWE employs around 19,000 people worldwide and has a clear target: to get to net zero by 2040. On its way there, the company has set itself ambitious targets for all activities that cause greenhouse gas emissions. The Science Based Targets initiative has confirmed that these emission reduction targets are in line with the Paris Agreement. Very much in the spirit of the company's purpose: Our energy for a sustainable life.; ['Power Generation', ' Renewable Energies', 'Gas Fleet', 'Energy Trading', 'Hydrogen']; ['#teamrwe']
Classification: Energy General
Text: Goldman Sachs; At Goldman Sachs, we believe progress is everyone's business. That's why we commit our people, capital and ideas to help our clients, shareholders and the communities we serve to grow.Founded in 1869, Goldman Sachs is a leading global investment banking, securities and investment management firm. Headquartered in New York, we maintain offices in all major financial centers around the world. More about our company can be found at www.goldmansachs.com. For insights on developments currently shaping markets, industries and the global economy, subscribe to BRIEFINGS, a weekly email from Goldman Sachs. Copy and paste this link into your browser to sign up: http://link.gs.com/Qxf3.com/social-media-disclosures; []; ['#mynamemyheritage', '#makethingspossible']
Classification: Other Sectors
Text: PPC Solar (Paradise Power Company); PPC SOLAR excels in the engineering, procurement and construction (EPC) of energy transition solutions including photovoltaic installation, EV charging infrastructure and energy storage solutions. With over 40-years of local presence PPC has built strong relationships within the region for unsurpassed value. Headquartered in Taos, New Mexico, with a branch office in Albuquerque we serve the Southern, Central and Northern New Mexico Regions along with Southern Colorado.; ['Photovoltaic', 'Solar', 'Renewable Energy', 'Solar Electric', 'PV ', 'EV Charging Stations', 'Energy Storage', 'battery based PV Systems', 'ChargePoint Partner', 'off-grid', 'Residential', 'Commercial', 'Utility', 'Operations& Maintenance', 'electric vehicle charging']; ['#newmexico', '#photovoltaics', '#evcharging']
Classification: Solar, Electric Vehicles, Battery
Text: PT Bukit Asam Tbk; PT Bukit Asam Tbk (IDX: PTBA) is a state-owned enterprise that operates in mining industry, particularly coal mining, located in Tanjung Enim, South Sumatra.
In line with the Company's vision to become a world-class energy company, Bukit Asam continues to be committed to increasing added value for the Company, shareholders, and all stakeholders of the Company.; ['Indonesia-State Owned Coal Mining Company', 'Coal Mining', 'Coal Trading', 'Energy']; ['#energi', '#sustainability', '#transformasidigital']
Classification: Coal
Text: Climeworks empowers people and companies to fight global warming by offering carbon dioxide removal as a service via direct air capture (DAC) technology. Climeworks' DAC facilities run exclusively on clean energy, and our modular CO_2 collectors can be stacked to build machines of any capacity.
Classification: Direct Air Capture
Text: Cisco; Cisco (NASDAQ: CSCO) enables people to make powerful connections–whether in business, education, philanthropy, or creativity. Cisco hardware, software, and service offerings are used to create the Internet solutions that make networks possible–providing easy access to information anywhere, at any time. Cisco was founded in 1984 by a small group of computer scientists from Stanford University. Since the company's inception, Cisco engineers have been leaders in the development of Internet Protocol (IP)-based networking technologies. Today, with more than 71,000 employees worldwide, this tradition of innovation continues with industry-leading products and solutions in the company's core development areas of routing and switching, as well as in advanced technologies such as home networking, IP telephony, optical networking, security, storage area networking, and wireless technology. In addition to its products, Cisco provides a broad range of service offerings, including technical support and advanced services. Cisco sells its products and services, both directly through its own sales force as well as through its channel partners, to large enterprises, commercial businesses, service providers, and consumers.; ['Networking', 'Wireless', 'Security', 'Unified Communication', 'Cloud', 'Collaboration', 'Data Center', 'Virtualization', 'Unified Computing Systems']; ['#lifeonwebex', '#wearecisco', '#bethebridge'] Classification: Computer and Electronic Products, Software, Other ICT
Text: Rio Tinto; We're finding better ways to provide the materials the world needs. Iron ore for steel. Low carbon aluminium for electric cars and smartphones. Copper for wind turbines, electric cars and the pipes that bring water to our home. Borates that help crops grow and titanium for paint.; ['mining', 'processing', 'exploration', 'metals', 'minerals', 'energy']
Classification: Iron and Steel, Raw Materials
{*Text to Classify*}

Table S24: Prompt used for the organization type classifier for organizations.

You are a research assistant classifying organization profiles on LinkedIn. Classify the organization into one or multiple of the following categories:
"Governmental Organization": "Public sector entity or agency", "Non Governmental Organization": "Non-profit, non-state civil organization", "International Organization": "Multinational governance or policy body", "Research Institute": "Non-university research body", "University": "Higher education and academic research institution", "Accelerator/Incubator": "Startup support program or ecosystem", "Bank": "Financial institution offering banking services", "Venture Capital": "Investment firm funding startups and innovation", "Other Financing Organization": "Non-bank financial services (e.g., real estate funds, private equity, pensin funds)", "Consulting": "Professional services firm offering expert advice", "Project Developer": "Company developing infrastructure or energy projects", "Manufacturer": "Entity producing physical goods or equipment", "Mining": "Entity involved in mineral or resource extraction", "Utility": "Company providing electricity, water, or gas services", "Service Provider": "Commercial firm delivering operational or technical services", "Lobby Group": "Organization advocating for specific policy interests", "Media Firm": "News or information dissemination organization", "Event Organizer": "Entity managing or hosting conferences and events", "Other": "Does not fit into any defined categories"
Use the label "Other" if the organization does not fit into any of the above categories.

Here are some exemplary classifications:
Text: Fraunhofer-Institut für Solare Energiesysteme ISE; The Fraunhofer Institute for Solar Energy Systems ISE in Freiburg, Germany is the largest solar research institute in Europe. With a staff of about 1400, we are committed to promoting a sustainable, economic, secure and socially just energy supply system based on renewable energy sources. We contribute to this through our main research areas of energy provision, energy distribution, energy storage and energy utilization. Through outstanding research results, successful industrial projects, spin-off companies and global collaborations, we are shaping the sustainable transformation of the energy system: https://www.ise.fraunhofer.de/en/publishing-notes.html; ['Photovoltaik', 'Energiesystemtechnik', 'Solarthermie', 'Gebäudeenergietechnik', 'Wasserstofftechnologien']; ['#energytransition', '#research', '#solar']
Classification: Research Institute
Text: Esken; We own two core assets; London Southend Airport and Stobart Energy.London Southend Airport is an award-winning airport serving London and the South East. It has ambitions plans to grow and the key ingredients in place to enable that growth. And; in Stobart Energy we have a transformational and maturing business which supplies fuel to biomass plants across the UK so that they can, in turn, create renewable energy.; ['Infrastructure and Support Services', 'Railway Maintenance', 'Biomass Energy', 'Aviation', 'Biomass'];
Classification: Service Organization
Text: LanzaTech; Where others see a dire choice, LanzaTech sees a trillion-dollar opportunity.The good news is after 15 years, north of a thousand patents, and millions of hours of pioneering scientific inquiry, LanzaTech has invented a technology big enough to meet the moment. One that transforms pollution into profit, and ensures that humans continue to prosper far into the post-pollution future.The science is state-of-the-art, but the idea is simple. We use nature to heal nature. First we capture carbon emissions. Then we feed them into bioreactors where trillions of carbon-hungry microbes go to work. These tiny dynamos eat the pollution and output valuable raw material commodities. (...). LanzaTech is turning it into an opportunity. Reducing emissions and making money for our customers — today. Let's transform our tired Lose-Lose climate debate into a Win-Win proposition. One that helps companies grow their revenue while helping the planet reach a post-pollution reality. LanzaTech — Welcome to the Post Pollution Future; ['chemical recycling', 'carbon emissions', 'air quality', 'circular economy', 'green chemistry', 'carbon recycling', 'climate action', 'fuels and chemicals']; ['#lanzatech', '#circulareconomy', '#carbonrecycling']
Classification: Manufacturer
Text: RWE; RWE is leading the way to a green energy world. With an extensive investment and growth strategy, the company will expand its powerful, green generation capacity to 50 gigawatts internationally by 2030. RWE is investing €50 billion gross for this purpose in this decade. The portfolio is based on offshore and onshore wind, solar, hydrogen, batteries, biomass and gas. RWE Supply & Trading provides tailored energy solutions for large customers. RWE has locations in the attractive markets of Europe, North America and the Asia-Pacific region. The company is responsibly phasing out nuclear energy and coal. Government-mandated phaseout roadmaps have been defined for both of these energy sources. RWE employs around 19,000 people worldwide and has a clear target: to get to net zero by 2040. On its way there, the company has set itself ambitious targets for all activities that cause greenhouse gas emissions. The Science Based Targets initiative has confirmed that these emission reduction targets are in line with the Paris Agreement. Very much in the spirit of the company's purpose: Our energy for a sustainable life.; ['Power Generation', ' Renewable Energies', 'Gas Fleet', 'Energy Trading', 'Hydrogen']; ['#teamrwe']
Classification: Utility
Text: Goldman Sachs; At Goldman Sachs, we believe progress is everyone's business. That's why we commit our people, capital and ideas to help our clients, shareholders and the communities we serve to grow. Founded in 1869, Goldman Sachs is a leading global investment banking, securities and investment management firm. Headquartered in New York, we maintain offices in all major financial centers around the world. More about our company can be found at www.goldmansachs.com. For insights on developments currently shaping markets, industries and the global economy, subscribe to BRIEFINGS, a weekly email from Goldman Sachs. Copy and paste this link into your browser to sign up: http://link.gs.com/Qxf3.com/social-media-disclosures; []; ['#mynamemyheritage', '#makethingspossible']
Classification: Bank
Text: PPC Solar (Paradise Power Company); PPC SOLAR excels in the engineering, procurement and construction (EPC) of energy transition solutions including photovoltaic installation, EV charging infrastructure and energy storage solutions. With over 40-years of local presence PPC has built strong relationships within the region for unsurpassed value. Headquartered in Taos, New Mexico, with a branch office in Albuquerque we serve the Southern, Central and Northern New Mexico Regions along with Southern Colorado.; ['Photovoltaic', 'Solar', 'Renewable Energy', 'Solar Electric', 'PV ', 'EV Charging Stations', 'Energy Storage', 'battery based PV Systems', 'ChargePoint Partner', 'off-grid', 'Residential', 'Commercial', 'Utility', 'Operations & Maintenance', 'electric vehicle charging']; ['#newmexico', '#photovoltaics', '#evcharging']
Classification: Manufacturer, Project Developer
Text: The ERA Foundation; The ERA Foundation is a non-profit organisation which supports engineering skills development and aims to bridge the gap between engineering research and its commercialisation.; ['Outreach', 'Policy', 'Supporting UK Manufacturing', 'Supporting Engineering in the UK']; ['#engineering', '#stemeducation', '#electech']
Classification: Non Governmental Organization
Text: Parkit Enterprise Inc.; Parkit Enterprise Inc. is engaged in the acquisition, optimization and asset management of income producing industrial properties in Canada and parking facilities across North America. The Company's shares are listed on TSX-V (Symbol: PKT) and on the OTC (Symbol: PKTEF).; ['Industrial Real Estate', 'Parking Assets']; ['#parkitenterprise']
Classification: Other Financing Organization
Text: PT Bukit Asam Tbk; PT Bukit Asam Tbk (IDX: PTBA) is a state-owned enterprise that operates in mining industry, particularly coal mining, located in Tanjung Enim, South Sumatra.
In line with the Company's vision to become a world-class energy company, Bukit Asam continues to be committed to increasing added value for the Company, shareholders, and all stakeholders of the Company.; ['Indonesia-State Owned Coal Mining Company', 'Coal Mining', 'Coal Trading', 'Energy']; ['#energi', '#sustainability', '#transformasidigital']
Classification: Governmental Organization, Mining
Text: The Economist; News and analysis with a global perspective. We're here to help you understand the world around you. To subscribe to The Economist go to: https://bit.ly/3OLFYsJ To make a request about your personal data visit: https://econ.st/2OZnq92; ['News', 'Analysis', 'Global Perspective']; ['#climatechange', '#sustainability', '#environment']
Classification: Media Firm
{*Text to Classify*}

Table S25: Performance of the relevance classifier for climate tech.

Classifier	Precision	Recall	F1-score	Number of true positives
non-relevant	0.99	0.98	0.99	538
relevant	0.95	0.98	0.96	186

Table S26: Performance of the collaboration classifier.

Classifier	Precision	Recall	F1-score	Number of true positives
Collaboration relevance				
non-relevant	0.97	0.97	0.97	69
relevant	0.94	0.94	0.94	31
Average	0.95	0.95	0.95	100
Technology classification				
Battery	0.94	1.00	0.97	17
Bioenergy with Carbon Capture and Story (BECCS)	1.00	1.00	1.00	11
Biochar	0.77	1.00	0.87	10
Biogas	1.00	0.93	0.97	15
Biofuels	0.92	1.00	0.96	12
Biomass	1.00	0.87	0.93	15
Carbon Capture And Storage (CCS)	1.00	1.00	1.00	12
Carbon Direct Removal (Other Solutions)	1.00	0.83	0.91	12
Concentrated Solar	1.00	1.00	1.00	11
Direct Air Capture (DAC)	0.91	0.91	0.91	11
Electric Aviation	0.91	0.91	0.91	11
Electric Shipping	0.83	1.00	0.91	10
Electric Vehicles	1.00	1.00	1.00	13
E-Fuels	1.00	0.83	0.91	12
Fuel Cell Aviation	1.00	1.00	1.00	10
Geothermal	0.86	1.00	0.92	12
Green Hydrogen	0.97	0.91	0.94	34
Hydro Energy	0.92	1.00	0.96	11
Marine Energy	0.77	1.00	0.87	10
Nuclear Fission	1.00	1.00	1.00	12
Nuclear Fusion	1.00	1.00	1.00	10
Offshore Wind	1.00	1.00	1.00	13
Railway	1.00	1.00	1.00	10
Solar	0.85	1.00	0.92	28
Sustainable Aviation Fuels (SAFs)	1.00	1.00	1.00	13
Waste to Heat	1.00	0.90	0.95	10
Wind (Onshore)	0.96	0.96	0.96	27
Micro average	0.94	0.96	0.95	382
Macro average	0.94	0.97	0.95	382
Collaboration type classification				
R&D collaborations	1.00	0.89	0.94	9
Demonstrations & pilots	1.00	0.88	0.94	17
First commercial deployments & product launches	1.00	0.91	0.95	11
Production & manufacturing	1.00	1.00	1.00	14
Offtake agreements	1.00	1.00	1.00	11
Adoption & deployments	0.93	1.00	0.96	13
Operations & maintenance	1.00	0.83	0.91	12
Grants	1.00	0.77	0.87	13
Equity Investments	0.93	1.00	0.96	13
Debt finance	1.00	1.00	1.00	10
Other unspecified finance	0.92	0.85	0.88	13
Spin-offs	0.90	1.00	0.95	9
Mergers & acquisitions	1.00	0.92	0.96	13
Joint ventures	1.00	0.93	0.96	14
Incubators & accelerator programs	1.00	1.00	1.00	11
Certification & approvals	1.00	1.00	1.00	10
Training	1.00	0.92	0.96	13
Micro average	0.98	0.93	0.96	206
Macro average	0.98	0.94	0.96	206

Table S27: Prompt used for the collaboration extraction and classification.

You are a research assistant classifying LinkedIn posts. Follow these steps:

1. **Determine if the post announces an innovation collaboration between the posting organization and other organizations (Yes/No).**

- Collaborations must explicitly involve a cooperation between entities for advancing a technology, OR a financial transaction, OR acquisitions, OR changes in ownership, OR any legally-binding partnership from one of the specified categories.

- Exclude joint events, panel discussions, or PR activities without specific innovation activities.

2. **If Yes, classify:**

- **Technologies:** Choose from the list: {"Biomass", "Biofuels", "Biogas", "Wind", "Offshore_Wind", "Solar", "Concentrated_Solar", "Waste_to_Heat", "Direct_Air_Capture", "Carbon_Capture_And_Storage", "Biochar", "BECCS", "Carbon_Direct_Removal", "Hydrogen" (including Fuel Cells for Green Energy), "Nuclear_Energy", "Nuclear_Fusion", "Hydro_Energy", "Geothermal", "Battery", "Electric_Vehicles", "Sustainable_Aviation_Fuels", "E_Fuels", "Marine_Energy" (tidal and wave electricity only!), "Heat_Pumps", "Railway", "Electric_Shipping", "Electric_Aviation", "Fuel_Cell_Aviation", "Other_Technology"}

- **Collaboration types:** Choose from the list: {"r_and_d_collaborations": "Joint efforts to conduct research and develop new technologies.", "demonstrations_and_pilots": "Testing and demonstrating developed technologies to prove feasibility. Includes the deployment of prototype and testing facilities.", "commercialisation_and_product_launches": "Announcements of first commercial deployments and new product launches.", "production_and_manufacturing": "Setting up or scaling facilities to manufacture technologies or products.", "offtake_agreements_and_futures": "Contracts for future sales or delivery of products.", "adoption_and_deployments": "Concrete deployments, construction of power plants, sales, or adoption of products and technologies in the market. This includes the construction of infrastructure or systems that enable the use of a technology.", "operations_and_maintenance": "Collaborations focused on running and maintaining systems or equipment.", "grants": "Grants must be mentioned explicitly.", "equity_investments": "Financial investments in exchange for ownership stakes in a company or project.", "loans": "Explicitly mentioned debt or loan financing provided for project financing, repaid with interest.", "other_unspecified_finance": "Any financial collaboration that does not fit the categories above.", "spin_offs": "New companies formed to commercialize a specific technology or idea.", "mergers_and_acquisitions": "Business consolidations where companies merge or are acquired.", "joint_ventures": "Only classify as a joint venture if the term 'joint venture' is explicitly mentioned in the announcement!", "incubators_and_accelerator_programs": "Programs supporting startups or early-stage ventures through mentorship and resources.", "certification_and_approvals": "Processes to obtain official recognition, regulatory approval, or standards compliance for technologies or products.", "training": "Training related to a technology provided from one organization to another."}

- **Core technology:** Whether the announcement is about the core technology or corresponding infrastructure, software and digital platforms, raw materials, recycling, or other complementary activities.

3. **If Yes, extract the relevant organizations** for the collaboration mentioned in the post from the list of referenced organizations.

Guidelines for Output:

- Use consistent formatting for responses. Only provide the classification. Do not repeat the post or add explanations.

- If multiple categories apply, include all relevant entries. In the innovation categories (r and d collaborations, demonstrations and pilots, commercialisation and product launches, production and manufacturing, sales agreements and futures), prioritize the most relevant.

- For financial collaborations, use other unspecified finance if the type of finance is unclear.

- Only classify technologies for tidal or wave electricity generation (and not shipping) as Marine Energy.

- Only classify airplanes and aviation projects with Fuel Cell Aviation.

- Do not change the format of the organization names in the referenced organizations list.

Examples:

Post: fraunhofer-gesellschaft: We support Emmvee Group as their solar technology partner in setting up a production facility to produce solar panels at scale; referenced_organizations=['fraunhofer-gesellschaft','Emmvee Group']

Answer: Yes: Technologies = ['Solar'], Collaboration_types = ['production_and_manufacturing'], Core_technology = ['core_technology'], Collaborating_organizations=['fraunhofer-gesellschaft','Emmvee Group']

Post: soato: Bill Nicholson presented a coating technology at CPhI. coating-society brix-technologies.

Answer: No: This is only a product announcement without specifying a collaboration.

Post: hydrogène-de-france: Milestones in Indonesia with u.s. international development finance corporation. Technical assistance to develop 22 hydrogen power plants. $1.5 billion potential investment; referenced_organizations=['hydrogène-de-france', 'us-idfc']

Answer: Yes: Technologies = ['Hydrogen'], Collaboration_types = ['other_unspecified_finance', 'offtake_agreements_and_futures'], Core_technology = ['core_technology'], Collaborating_organizations=['hydrogène-de-france', 'us-idfc']

Post: kengenkenya: KenGen Kenya has partnered with Nairobi Metropolitan Services (NMS) to develop a 45MW Waste to Heat Power Plant financed through a government grant; referenced_organizations=['kengenkenya', 'nairobi-metropolitan-services']

Answer: Yes: Technologies = ['Waste_to_Heat'], Collaboration_types = ['adoption_and_deployments','grants'], Core_technology = ['core_technology'], Collaborating_organizations=['kengenkenya', 'nairobi-metropolitan-services']

Post: vinci-concessions: Since 2021, we are partnering with Airbus to promote the use of hydrogen and accelerate the decarbonization of the aviation sector. In Japan, Kansai Airports and Airbus have recently signed a memorandum of understanding to explore the use of hydrogen at three airports we operate in the country; referenced_organizations=['vinci-concessions', 'airbus', 'kansai-airports']

Answer: Yes: Technologies = ['Hydrogen', 'Fuel_Cell_Aviation'], Collaboration_types = ['demonstrations_and_pilots'], Core_technology = ['core_technology'], Collaborating_organizations=['vinci-concessions', 'airbus', 'kansai-airports']

Post: volvo: Bosch at the World Business Council event highlighting joint efforts.

Answer: No: Participating in joint conferences and events does not count.

Post: faurencia: In partnership with our joint venture Symbio, we showcase tested prototypes for low and zero emission vehicles, including hydrogen and electric vehicles. Hydrogen News Hydrogen Daily; referenced_organizations=['faurencia', 'https://www.linkedin.com/company/symbio/', 'hydrogen-news', 'hydrogen-daily']

Answer: Yes: Technologies = ['Hydrogen', 'Electric_Vehicles'], Collaboration_types = ['joint_ventures', 'demonstrations_and_pilots'], Core_technology = ['core_technology'], Collaborating_organizations=['faurencia', 'https://www.linkedin.com/company/symbio/']

Post: Orbital Marine Power: The world's most powerful tidal turbine is installed, generating power into the UK grid. Made possible by European Commission and Horizon 2020 funding; referenced_organizations=['orbital-marine-power-ltd', 'european-commission', 'horizon-2020']

Answer: Yes: Technologies = ['Marine_Energy'], Collaboration_types = ['adoption_and_deployments', 'grants', 'equity_investments'], Core_technology = ['core_technology'], Collaborating_organizations=['orbital-marine-power-ltd', 'european-commission', 'horizon-2020']

Post: Amarenco: SolarPower Europe launches French version of the Agrisolar Best Practice Guidelines, with the support of French industry! The report explores real-world examples of Agrisolar projects in the EU. At Amarenco, we are extremely proud to be a part of this with SolarPower Europe; referenced_organizations=['SolarPower Europe', 'Amarenco']

Answer: No: This post is about the publication of a report.

Post: AgriVijay: Presenting Multi Utility Biogas Powered Farming Tool power launched in partnership with Sukoon Solutions by AgriVijay! Key benefits: Join the sustainable farming revolution today! Sukoon Solutions AIC-JKLU NITI GOVERNMENT OF INDIA UNICEF Confederation of Indian Industry SIDBI (Small Industries Development Bank of India) Social Alpha Omnivore; referenced_organizations=['AgriVijay', 'sukoon-solutions', 'unicef', 'social-alpha', 'omnivore-partners']

Answer: Yes: Technologies = ['Biogas'], Collaboration_types = ['commercialisation_and_product_launches'], Core_technology = ['core_technology'], Collaborating_organizations=['AgriVijay', 'sukoon-solutions']

Post: siemens-energy: Today, we announce our new partnerships: with ABB we will develop a new generation of electric vehicle charging technologies and with SolarEdge we will construct a new solar farm in the US; referenced_organizations=['siemens-energy', 'abb', 'solaredge']

Answer: Yes: [Technologies = ['Electric_Vehicles'], Collaboration_types = ['r_and_d_collaborations'], Core_technology = ['infrastructure'], Collaborating_organizations=['siemens-energy', 'abb']], [Technologies = ['Solar'], Collaboration_types = ['production_and_manufacturing'], Core_technology = ['core_technology'], Collaborating_organizations=['siemens-energy', 'solaredge']]

Post: grundon-waste-management-ltd: We're delighted to announce we have just invested around £200,000 in two state-of-the-art JCB electric Teletruk forklifts by JBC; referenced_organizations=['grundon-waste-management-ltd', 'jcb', 'pyroban']

Answer: Yes: Technologies = ['Electric_Vehicles'], Collaboration_types = ['adoption_and_deployments'], Core_technology = ['core_technology'], Collaborating_organizations=['grundon-waste-management-ltd', 'jcb', 'pyroban']

{*Text to Classify*}

Table S28: Top 20 organizations by network centrality metric for the Pre-IRA (01.2020–06.2022) and the Post-IRA periods (07.2022–12.2024) for the nuclear fusion innovation network. Centrality scores are reported in brackets next to the organizations' LinkedIn names. Note that degree centrality is relative to the total number of possible partnerships in the network.

	Pre-IRA				**Post-IRA**			
Rank	Degree Centrality	Betweenness Centrality	Eigenvector Centrality	Closeness Centrality	Degree Centrality	Betweenness Centrality	Eigenvector Centrality	Closeness Centrality
1	ITER Organization (0.3156)	ITER Organization (0.2817)	ITER Organization (0.2084)	ITER Organization (0.4241)	UK Atomic Energy Authority (0.2139)	UK Atomic Energy Authority (0.2028)	UK Atomic Energy Authority (0.2645)	UK Atomic Energy Authority (0.4498)
2	Assystem (0.2021)	UK Atomic Energy Authority (0.0929)	Fusion for Energy (0.1923)	Assystem (0.3735)	ITER Organization (0.1604)	Tokamak Energy (0.1087)	Assystem (0.2057)	Tokamak Energy (0.4346)
3	Fusion for Energy (0.1879)	General Fusion (0.0808)	Assystem (0.1901)	Jacobs (0.3656)	Tokamak Energy (0.1533)	ITER Organization (0.1027)	Midlands Engine (0.1573)	ITER Organization (0.4208)
4	ENEA (0.1773)	Westinghouse Electric Company (0.0795)	ENEA (0.1867)	ENEA (0.3642)	U.S. DOE (0.1497)	U.S. DOE (0.1004)	ERA (0.1566)	U.S. DOE (0.4168)
5	Jacobs (0.1560)	Commonwealth Fusion Systems (0.0745)	ASG Superconductors S.p.A. (0.1859)	Fusion for Energy (0.3574)	Fusion for Energy (0.1194)	Max Planck Institute (0.0585)	Midlands Innovation (0.1560)	EUROfusion (0.4033)
6	Walter Tosto S.p.A. (0.1489)	Assystem (0.0667)	Ferrovial (0.1855)	Atkins (0.3548)	Max Planck Institute (0.1194)	EUROfusion (0.0521)	Birmingham Energy Institute (0.1560)	Max Planck Institute (0.4022)
7	Ferrovial (0.1489)	Jacobs (0.0644)	RAZEL-BEC (0.1855)	Westinghouse Electric Company (0.3535)	Assystem (0.1176)	Fusion for Energy (0.0481)	EBRI (0.1560)	IAEA (0.3989)
8	RAZEL-BEC (0.1489)	ENEA (0.0596)	Walter Tosto S.p.A. (0.1848)	UK Atomic Energy Authority (0.3496)	EUROfusion (0.1123)	Commonwealth Fusion Systems (0.0452)	Cranfield University (0.1560)	Kyoto Fusioneering (0.3981)
9	UK Atomic Energy Authority (0.1454)	eni (0.0581)	Apave (0.1839)	Walter Tosto S.p.A. (0.3483)	IAEA (0.1016)	Renaissance Fusion (0.0449)	Keele University (0.1560)	PPPL (0.3971)
10	Consorzio RFX (0.1454)	First Light Fusion (0.0409)	CNIM (0.1835)	Ferrovial (0.3470)	PPPL (0.0856)	Oxford Sigma (0.0415)	CREST (0.1560)	Assystem (0.3893)
11	ASG Superconductors S.p.A. (0.1454)	Fusion for Energy (0.0367)	Elytt Energy (0.1835)	RAZEL-BEC (0.3470)	Focused Energy (0.0838)	General Fusion (0.0414)	Univ. of Nottingham Energy Inst. (0.1560)	Oxford Sigma (0.3865)
12	SIMIC (0.1418)	IREC (0.0342)	SIMIC (0.1829)	ASG Superconductors S.p.A. (0.3464)	Renaissance Fusion (0.0820)	IAEA (0.0383)	Univ. of Warwick (0.1560)	Jacobs (0.3808)
13	Apave (0.1418)	Culham Science Centre (0.0337)	Atkins (0.1821)	SIMIC (0.3458)	Oxford Sigma (0.0784)	PPPL (0.0380)	WMG, Univ. of Warwick (0.1560)	General Atomics (0.3791)
14	CNIM (0.1383)	General Atomics (0.0336)	ENGIE (0.1795)	Apave (0.3445)	General Fusion (0.0784)	HB11 Energy (0.0366)	Univ. of Leicester (0.1560)	Focused Energy (0.3752)
15	Elytt Energy (0.1383)	Oak Ridge NL (0.0298)	Iberdrola (0.1795)	CNIM (0.3439)	Consorzio RFX (0.0766)	Assystem (0.0365)	Ansaldo Nuclear (0.1499)	Renaissance Fusion (0.3749)
16	Atkins (0.1383)	Consorzio RFX (0.0296)	Ansaldo Energia (0.1618)	Elytt Energy (0.3439)	LLNL (0.0749)	LLNL (0.0360)	EDF (0.1495)	Fusion for Energy (0.3720)
17	Ansaldo Energia (0.1348)	Tokamak Energy (0.0292)	VINCI Construction (0.1604)	Iberdrola (0.3421)	ENEA (0.0749)	Kyoto Fusioneering (0.0338)	Equilibrion (0.1438)	Commonwealth Fusion Systems (0.3711)
18	Iberdrola (0.1277)	Dept. for Science, Innovation & Tech (0.0288)	Consorzio RFX (0.1576)	ENGIE (0.3421)	Jacobs (0.0695)	Novatron Fusion Group (0.0297)	Midlands Net Zero Hub (0.1392)	ENEA (0.3692)
19	ENGIE (0.1277)	Kyoto Fusioneering (0.0255)	Veolia (0.1566)	Consorzio RFX (0.3414)	DIFFER (0.0660)	Focused Energy (0.0282)	Rolls-Royce SMR (0.1392)	Gauss Fusion (0.3667)
20	Veolia (0.1241)	U.S. DOE (0.0250)	EAG (0.1552)	Westinghouse Mangiarotti (0.3378)	First Light Fusion (0.0642)	ENEA (0.0220)	Cogent Skills (0.1392)	Atkins (0.3661)

Table S29: Top 20 organizations by network centrality metric for the Pre-IRA (01.2020–06.2022) and the Post-IRA periods (07.2022–12.2024) for the direct air capture (DAC) innovation network. Centrality scores are reported in brackets next to the organizations' LinkedIn names. Note that degree centrality is relative to the total number of possible partnerships in the network.

	Pre-IRA				**Post-IRA**			
Rank	Degree Centrality	Betweenness Centrality	Eigenvector Centrality	Closeness Centrality	Degree Centrality	Betweenness Centrality	Eigenvector Centrality	Closeness Centrality
1	Climeworks (0.2318)	Climeworks (0.3549)	Climeworks (0.5159)	Climeworks (0.3732)	U.S. DOE (0.1163)	Climeworks (0.1441)	U.S. DOE (0.2698)	U.S. DOE (0.3446)
2	Carbon Engineering (0.1213)	Carbon Engineering (0.1651)	Carbon Engineering (0.2171)	Carbon Engineering (0.3171)	Climeworks (0.1131)	U.S. DOE (0.1328)	Climeworks (0.2400)	Climeworks (0.3386)
3	Breakthrough Energy (0.0755)	U.S. DOE (0.1170)	Breakthrough Energy (0.2060)	Breakthrough Energy (0.3097)	CarbonCapture (0.0672)	Capture6 (0.0617)	Heirloom (0.2185)	Heirloom (0.3301)
4	U.S. DOE (0.0755)	Soletair Power (0.1100)	U.S. DOE (0.1939)	Carbfix (0.3042)	Heirloom (0.0651)	Removr (0.0523)	CarbonCapture (0.2064)	Avnos (0.3194)
5	Stripe (0.0539)	Mission Zero Tech (0.0760)	Stripe (0.1542)	Shopify (0.2903)	Capture6 (0.0598)	Heirloom (0.0482)	Fluor Corp (0.1691)	Aircapture (0.3157)
6	Soletair Power (0.0539)	Breakthrough Energy (0.0749)	European Commission (0.1487)	Soletair Power (0.2896)	RepAir (0.0566)	1PointFive (0.0457)	Avnos (0.1665)	Stripe (0.3155)
7	Carbfix (0.0458)	Stripe (0.0552)	Carbfix (0.1459)	U.S. DOE (0.2892)	Removr (0.0502)	CarbonCapture (0.0434)	Stripe (0.1641)	CarbonCapture (0.3127)
8	Mission Zero Tech (0.0404)	Climate-KIC (0.0444)	Microsoft (0.1420)	McKinsey & Co. (0.2870)	Stripe (0.0502)	RepAir (0.0431)	8 Rivers (0.1601)	Removr (0.3073)
9	CarbonCapture (0.0404)	Optimus Plus (0.0444)	BCG (0.1420)	Heirloom (0.2870)	Airhive (0.0470)	Greenlyte (0.0428)	Removr (0.1584)	Airhive (0.3045)
10	1PointFive (0.0377)	Heirloom (0.0413)	Shopify (0.1251)	Stripe (0.2844)	8 Rivers (0.0470)	Shell (0.0420)	Aircapture (0.1529)	Shopify (0.3043)
11	Oxy (0.0377)	Carbfix (0.0370)	Heirloom (0.1185)	CarbonCure (0.2834)	Shell (0.0470)	Deep Sky (0.0401)	Carbfix (0.1525)	RepAir (0.3042)
12	PNNL (0.0377)	CINEA (0.0344)	CarbonCure (0.1184)	Puro.earth (0.2760)	Third Derivative (0.0438)	Stripe (0.0380)	Shopify (0.1525)	Carbfix (0.3035)
13	European Commission (0.0350)	Net Zero Tech Centre (0.0308)	McKinsey & Co. (0.1175)	44.01 (0.2757)	Carbfix (0.0438)	Octavia Carbon (0.0362)	RMI (0.1497)	Third Derivative (0.3032)
14	CINEA (0.0323)	Puro.earth (0.0265)	Verdox (0.1086)	Verdox (0.2750)	Shopify (0.0438)	Airhive (0.0307)	Calcite (0.1484)	RMI (0.3026)
15	Heirloom (0.0323)	Chevron (0.0247)	American Airlines (0.1026)	European Commission (0.2743)	1PointFive (0.0427)	Carbyon (0.0293)	Sustaera (0.1474)	8 Rivers (0.3013)
16	Net Zero Tech Centre (0.0296)	44.01 (0.0225)	ArcelorMittal (0.1026)	Microsoft (0.2733)	Avnos (0.0427)	Third Derivative (0.0279)	LanzaTech (0.1257)	Sustaera (0.3003)
17	Shopify (0.0296)	Black & Veatch (0.0206)	Bank of America (0.1026)	BCG (0.2733)	Greenlyte (0.0427)	NeoCarbon (0.0277)	Twelve (0.1169)	Battelle (0.2995)
18	CarbonCure (0.0296)	CarbonCapture (0.0203)	BlackRock (0.1026)	Alphabet (0.2707)	Fluor Corp (0.0427)	LanzaTech (0.0252)	Microsoft (0.1151)	Deep Sky (0.2978)
19	GIC (0.0296)	XPRIZE (0.0189)	GM (0.1026)	Meta (0.2707)	Google (0.0406)	Aircapture (0.0233)	PNNL (0.1125)	Calcite (0.2977)
20	Verdox (0.0296)	Sargent & Lundy (0.0182)	Alphabet (0.1009)	CCB Energy (0.2700)	Aircapture (0.0406)	Battelle (0.0232)	Google (0.1109)	Fluor Corp (0.2974)

Table S30: Top 20 organizations by network centrality metric for the Pre-IRA (01.2020–06.2022) and the Post-IRA periods (07.2022–12.2024) for the green hydrogen innovation network. Centrality scores are reported in brackets next to the organizations' LinkedIn names. Note that degree centrality is relative to the total number of possible partnerships in the network.

	Pre-IRA				**Post-IRA**			
Rank	Degree Centrality	Betweenness Centrality	Eigenvector Centrality	Closeness Centrality	Degree Centrality	Betweenness Centrality	Eigenvector Centrality	Closeness Centrality
1	Air Liquide (0.0681)	Air Liquide (0.0653)	Air Liquide (0.2030)	Air Liquide (0.3977)	Air Liquide (0.0494)	European Commission (0.0463)	Air Liquide (0.1603)	Air Liquide (0.4100)
2	ENGIE (0.0598)	Shell (0.0628)	ENGIE (0.1766)	ENGIE (0.3940)	Clean Hydrogen Partnership (0.0477)	Air Liquide (0.0452)	Clean Hydrogen Partnership (0.1507)	European Commission (0.4081)
3	Shell (0.0545)	ENGIE (0.0613)	Shell (0.1509)	Shell (0.3919)	European Commission (0.0474)	Shell (0.0435)	European Commission (0.1478)	Shell (0.4069)
4	Siemens Energy (0.0432)	Ballard Power Systems (0.0453)	Siemens Energy (0.1402)	Siemens Energy (0.3815)	Shell (0.0429)	Siemens Energy (0.0329)	ENGIE (0.1463)	ENGIE (0.3990)
5	Ballard Power Systems (0.0424)	Siemens Energy (0.0359)	TotalEnergies (0.1344)	TotalEnergies (0.3805)	ENGIE (0.0391)	Clean Hydrogen Partnership (0.0328)	TotalEnergies (0.1388)	Siemens Energy (0.3985)
6	TotalEnergies (0.0409)	toyota (0.0317)	European Commission (0.1322)	European Commission (0.3789)	TotalEnergies (0.0384)	Ballard Power Systems (0.0293)	Shell (0.1311)	Clean Hydrogen Partnership (0.3985)
7	European Commission (0.0364)	TotalEnergies (0.0295)	Clean Hydrogen Partnership (0.1176)	Ballard Power Systems (0.3755)	Airbus (0.0354)	Airbus (0.0256)	RWE (0.1172)	TotalEnergies (0.3962)
8	Clean Hydrogen Partnership (0.0351)	Snam S.p.A. (0.0262)	Equinor (0.1111)	Clean Hydrogen Partnership (0.3734)	RWE (0.0343)	TotalEnergies (0.0254)	Lhyfe (0.1062)	RWE (0.3928)
9	ABB (0.0337)	Hazer Group (0.0239)	EDF (0.1099)	Nel Hydrogen (0.3711)	Siemens Energy (0.0334)	ENGIE (0.0249)	Airbus (0.1008)	Ballard Power Systems (0.3928)
10	Snam S.p.A. (0.0335)	European Commission (0.0239)	Ballard Power Systems (0.1094)	toyota (0.3707)	DNV (0.0320)	bp (0.0231)	Siemens Energy (0.0994)	Airbus (0.3901)
11	Equinor (0.0325)	Clean Hydrogen Partnership (0.0228)	Nel Hydrogen (0.1053)	Equinor (0.3704)	Ballard Power Systems (0.0316)	Lhyfe (0.0217)	Ballard Power Systems (0.0973)	bp (0.3869)
12	Gasunie (0.0308)	Nel Hydrogen (0.0219)	Snam S.p.A. (0.1048)	Snam S.p.A. (0.3676)	Lhyfe (0.0313)	DNV (0.0214)	bp (0.0928)	Lhyfe (0.3863)
13	Nel Hydrogen (0.0307)	ABB (0.0216)	McPhy (0.1027)	DNV (0.3671)	ADEME (0.0301)	RWE (0.0213)	Port of Rotterdam (0.0915)	Linde (0.3845)
14	EDF (0.0307)	Equinor (0.0202)	ABB (0.1019)	Linde (0.3663)	bp (0.0291)	U.S. DOE (0.0205)	GRTgaz (0.0905)	DNV (0.3842)
15	toyota (0.0300)	Plug Power (0.0192)	Yara International (0.0970)	Airbus (0.3663)	Equinor (0.0266)	Linde (0.0158)	Equinor (0.0903)	Nel Hydrogen (0.3839)
16	Enagás (0.0300)	Ryze Hydrogen (0.0178)	DNV (0.0961)	EDF (0.3654)	Port of Rotterdam (0.0259)	Enagás (0.0134)	DNV (0.0894)	Equinor (0.3809)
17	TNO (0.0290)	DNV (0.0167)	Linde (0.0951)	Cummins Inc. (0.3639)	Linde (0.0238)	Nel Hydrogen (0.0132)	ADEME (0.0886)	Air Products (0.3789)
18	DNV (0.0270)	Enagás (0.0158)	bp (0.0947)	ABB (0.3637)	CEA (0.0228)	Air Products (0.0128)	Linde (0.0886)	Port of Rotterdam (0.3782)
19	RWE (0.0260)	Airbus (0.0156)	TNO (0.0947)	Yara International (0.3625)	Enagás (0.0228)	Equinor (0.0127)	McPhy (0.0836)	Enagás (0.3767)
20	Airbus (0.0253)	EDF (0.0153)	Gasunie (0.0938)	RWE (0.3618)	European Union (0.0227)	European Union (0.0127)	Enagás (0.0808)	European Union (0.3753)