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Quantifying knowledge spillovers from advances in negative emissions technologies

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Quantifying knowledge spillovers from advances in negative emissions technologies

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Abstract

Negative emissions technologies (NETs) feature prominently in most scenarios that halt climate change and deliver on the Paris Agreements temperature goal. As of today, however, their maturity and desirability are highly debated. Since the social value of new technologies depends on how novel knowledge fuels practical solutions, we take an innovation network perspective to quantify the multidimensional nature of knowledge spillovers generated by twenty years of research in NETs. In particular, we evaluate the likelihood that scientific advances across eight NET domains stimulate (i) further production of knowledge, (ii) technological innovation, and (iii) policy discussion. Taking as counterfactual scientific advances not related to NETs, we show that NETs-related research generates overall significant, positive knowledge spillovers within science and from science to technology and policy. At the same time, stark differences exist across carbon removal solutions. For example, the ability to turn scientific advances in NETs into technological developments is a nearly exclusively feature of Direct Air Capture (DAC), while Bio-energy with Carbon Capture and Storage (BECCS) lags behind. Conversely, BECCS and Blue Carbon (BC) have gained relative momentum in the policy and public debate, vis-à-vis limited spillovers from advances in DAC to policy. Moreover, both scientific advances and collaborations cluster geographically by type of NET, which might affect large-scale diffusion. Finally, our results suggest the existence of coordination gaps between NET-related science, technology, and policy.

1 Introduction

There is increasingly robust evidence that meeting ambitious climate targets, perhaps with limited temperature overshooting [1], will require removing large stocks of carbon dioxide from the atmosphere [2, 3]. Tackling climate change by removing CO2 from the atmosphere has been a tantalizing idea for quite some time [4]. Planting trees, or more precisely, designing forest management programs, has probably been the first solution to arise [5]. Over time though, a broader set of technical solutions have been developed, generally going under the label of *Negative Emissions Technologies* (NETs).

The large majority of Integrated Assessment Models (IAMs) now mention carbon removal as a pivotal element to meet the Paris Agreement requirements and thus tackle global warming [6, 7, 3]. According to these models, the transition toward zero emissions will require the extensive deployment of NETs to balance the inevitable difficulties of cutting short-term emissions even more drastically [8]. Furthermore, NETs might contribute to smooth out the so-called green transition, which will prove challenging from an economic, social, technological, and, of course, political perspective [9].

As of today, there are doubts on the possibility of immediate large-scale deployment of NETs, and their use as technical or policy panacea could not only be implausible, but even hazardous [10, 11, 12, 13]. The inclusion of these technologies in the design of climate policy pathways could risk delivering misleading guidelines if it underestimates the long and uncertain process that moves from basic research to the systemic diffusion of complex technical artifacts [14, 15, 16, 17, 18, 19]. In addition, little is known about how NETs at full regime could interact with other Sustainable Development Goals (SDGs) [15, 20]. NETs are indeed a peculiar set of technologies, whose economic value and market size largely depends on the strength of current and future climate policy, as well as from the global trajectory of emissions [21]. Against this backdrop, the available evidence about how different NETs could develop and diffuse is inconclusive.

Our paper provides new evidence about the relationships between scientific research in NETs, its diffusion and policy coverage, as well as their technological developments. In particular, we quantify the likelihood that scientific advances in NETs research (i) stimulate the production of further knowledge, (ii) foster technological innovation, and (iii) enter the policy debate. Moreover, we investigate the geographical distribution of NETs-related knowledge production, using relative comparative advantage and network analytic measures to identify the scientific specializations of countries and single out the main research hubs of the global innovation system.

Our paper contributes to a recent stream of studies acknowledging a relatively marginal role of NETs-related research within the broader climate discourse [22], and emphasise the need to better understand the scientific trends, the diffusion and up-scaling issues of NETs [23, 24, 25], as well as their broader economic challenge. Different NETs have been mostly evaluated along five dimensions (Figure 1**B**): negative emissions potential (i.e., Gt Ceq per year), energy and natural resource requirements (i.e., land and water use) and economic costs (US$ per t Ceq) [26, 27]. Overall, no universally superior option has been identified [28]. This paper provides novel dimensions to the multi-faceted comparison of various carbon removal technologies and provides the first estimates of knowledge spillovers generated by research in NETs.

We focus on the following list of options (see Figure 1**A** and Table S1 for a summary description): Afforestation and Reforestation (AR), Bio-energy with Cabon Capture and Storage (BECCS), Biochar, Blue carbon (BC), Direct Air Capture (DAC), Enhanced weathering (EW), Ocean fertilization (OF), and Soil carbon sequestration (SCS). DAC does not explicitly include storage options [29]; see Section 4.1 and S1 for more details.

We measure knowledge spillovers by using citations networks, as is standard in the innovation and applied economics literature [30, 31, 32]. Given the critical role played by climate-related technologies, we move beyond the standard citation counts to incorporate knowledge flows to practical innovations (i.e., patents) and the public discourse (i.e., policy documents) [33, 34, 35]. We also include the broader public impact of NETs research through different media channels to take into account a more complete and multidimensional set of knowledge spillovers. More in detail, by analyzing 20 years of academic literature via network and regression techniques [36, 37], we first provide a quantitative comparison of the impact of different NETs. Next, we focus on knowledge spillovers of NETs research in science, technology, and policy. Finally, we provide additional geographical and network analyses to study the spatial heterogeneity of cities and countries that can serve as research hubs for supporting future collaborations.

In extreme synthesis, by unpacking the multidimensional impact of knowledge spillovers, this paper suggests the existence of coordination gaps between science, technology and policy in the domain of carbon removal solutions. Our results show that (i) knowledge spillovers in science play a non-negligible role in the development of negative emissions solutions, (ii) in terms of impact, NETs are characterized by great heterogeneity, and only very few options are substantially linked to marketplace inventions, and (iii) negative emissions research activities are geographically concentrated around hubs with different specialisations from the viewpoint of the global division of labour. Interestingly, DAC appears as the most promising solution concerning technological developments (as indicated by patent citations); however, it is still relatively overlooked by policymakers (as indicated by policy reports citations).

A

Negative Emissions Technology	NET	References*
Afforestantion & Reforestation	**AR**	[Smith et al., 2016, Fuss et al., 2018]
Bio-energy with Carbon Capture and Storage	**BECCS**	[Smith et al., 2016, Fuss et al., 2018]
Biochar	**Biochar**	[Smith, 2016, Fuss et al., 2018]
Blue Carbon	**BC**	[Fuss et al., 2018, Bertram et al., 2021]
Direct Air Capture	**DAC**	[Smith et al., 2016, Fuss et al., 2018]
Enhanced Weathering	**EW**	[Smith et al., 2016, Fuss et al., 2018]
Ocean Fertilization	**OF**	[Strong et al., 2009, Fuss et al., 2018]
Soil Carbon Sequestration	**SCS**	[Smith, 2016, Fuss et al., 2018]

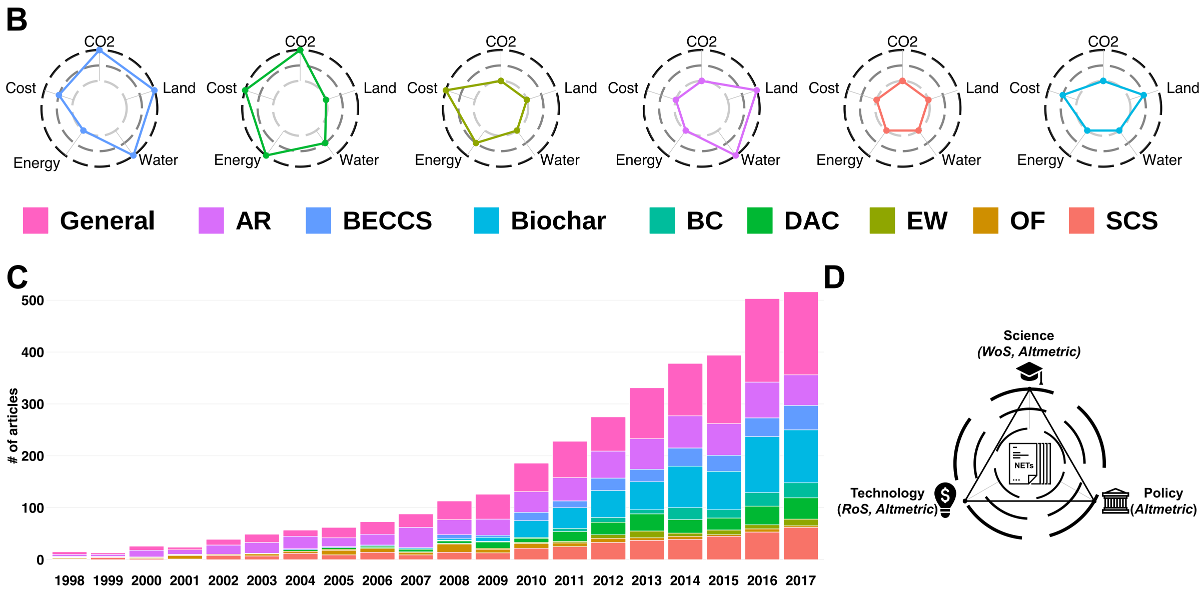

Figure 1: Negative emissions research. **(A)** The list of eight NETs included in our analysis. **(B)** A multidimensional comparison among different NETs (authors assessment adapted from [26, 27, 24]). **(C)** NETs articles from 1998 to 2017 collected though WoS text search. The category *General* is defined as a residual class including articles that match NETs keywords but do not specifically include words patterns in their titles or abstracts. **(D)** A stylized representation of the diverse sources of data necessary to keep track of knowledge flows to science, technology and policy. **(*)** The aforementioned references provide a detailed review of each NET. Summary radars concerning OF and BC not included (fewer conclusive information currently available [38, 39]).

2 Results

2.1 Knowledge base and spillovers: the landscape of negative emissions research

Technological and scientific breakthroughs are often the result of knowledge recombination processes, wherein past scientific advances become themselves knowledge components of future, often unexpected, innovative research paths [40, 17, 41, 42]. Our exploration of the NETs' research landscape starts by mapping the knowledge base (i.e., scientific fields on which NETs rely upon) and the potential spillover directions (i.e., scientific sub-fields influenced by NETs research developments). To identify them, we collected a large amount of bibliometric information related to NETs articles published in scientific journals (see section 4.1). We retrieve NETs papers by querying Web of Science (WoS) on the basis of keywords and their combinations in titles and abstracts [22, 23]. From 1998 to 2017, we collect 3301 published articles, distinguishing eight different NETs and considering a general residual category. Figure 1**c** shows the growing number of publications per year, with details for the different NETs. Next, we collect citations data from scientific papers, patents, and policy documents, along with non-technical media mentions (e.g., in social media, newspapers, blogs). To do so, we integrate several data sources, namely: Web of Science (WoS), Reliance on Science (RoS) and Altmetric (see sections 4.1 and S1 for more details). Figure 1**d** provides a schematic representation of the different sources of data used in our analysis to keep track of the multidimensionality of knowledge spillovers.

Negative emissions technologies are not all alike: crucial differences have been reported in relation to measurement, verification, accounting, and durability of carbon stored [43], as well as to costs and requirements [26, 27]. Against this background, we investigate the heterogeneity that characterizes NETs' knowledge base and spillover directions (Figure 2). Nature-based and technology-based approaches differ in both aspects. Figures 2**A,B,C,D** show a qualitative comparison between two nature-based methods (i.e., forest management and soil carbon sequestration) with the most popular technological solutions (BECCS and DAC). As expected, nature-based NETs are scientifically grounded in soil science and ecology, while solutions such as BECCS and DAC are engineering-driven methods. More interestingly, NETs build on different scientific fields, and the directions of potential spillovers follow accordingly. To better illuminate this, we show the overlap rates among subjects most frequently reported in the knowledge base (Figure 2**E**) and in set of spillover directions of each NETs pair (Figure 2**F**). Overall, our descriptive observation signals a prominent feature of NETs: the scientific heterogeneity of their knowledge base closely reflects the direction of spillovers effects. Some NETs can certainly be compatible in applications, but they are not synergic in the knowledge they develop and build upon.

In the following sections, we investigate the impact of negative emissions research on several dimensions, revealing that NETs generate substantial but heterogeneous spillovers, and that research activities are not evenly distributed from a geographical perspective.

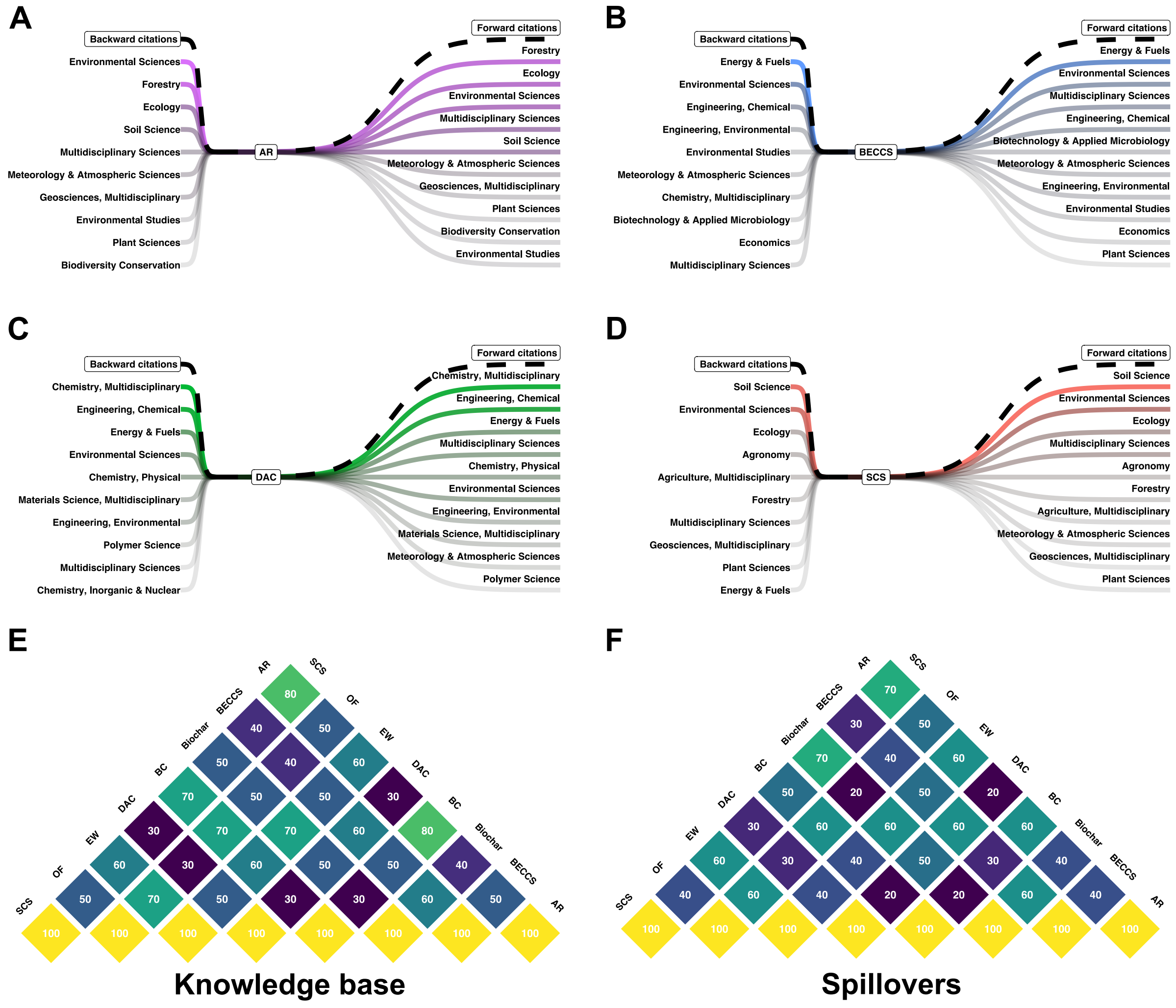

Figure 2: NETs knowledge base and spillovers. **(A–D)** Flows diagrams for AR, BECCS, DAC, and SCS. Top 10 WoS subjects that affect (backward citations) and are affected (forward citations) by NETs research. The first ten subjects comprise the large majority of citations (see figure S6 for details). **(A)** Afforestation and Reforestation – AR. **(B)** Bio-energy with Carbon Capture ans Storage – BECCS. **(C)** Direct Air Capture – DAC. **(D)** Soil Carbon Sequestration – SCS. **(E)** Matrix of overlapping subjects in NETs knowledge base (% values). **(F)** Matrix of overlapping subjects in NETs knowledge spillovers (% values). Full list of flows charts included in S5.

2.2 Multidimensional impact of NETs research

As mentioned above, NETs comprise a heterogeneous group of carbon removal solutions stemming from a diversified range of scientific disciplines. In this section, by exploiting the richness of different sources of data, we characterize, for the first time, the multidimensional nature of NETs impact, measuring their spillovers within and beyond their scientific reach.

Our quantitative comparison among scientific articles relies on identifying suitable control groups. Therefore, we employ a matching procedure to construct a “baseline” control, including articles published in the same year and the same journal, not directly related to NETs. In addition, to better characterize the role of NETs within the broader climate change academic debate, we construct a second control group (i.e., “climate control”), following the same strategy but focusing on the climate change literature. (see section 4.1 and S2 for more detailed information related to our matching strategy). It is worth noticing that our matching procedure has the purpose of balancing the comparison taking into account articles of the same age and ideally the same quality. However, such a matching scheme does not guarantee an exact counterfactual; it ensures that we compare articles with some key common characteristics.

Using Altmeric data, we compute the normalized number of mentions for each NET to gauge how the different streams of research are covered in academic, policy, technical, and media outlets. Figure 3 summarizes a first quantitative comparison in terms of impact (with the control group fixed at 1): each radar chart (Figure 3**A–I**) shows the multidimensional impact profile that characterizes research articles belonging to different NETs. We perform the same empirical exercise using as benchmark the climate control group (see Figure S7). Two main observations must be made: first, as NETs are intrinsically different, their impact mirrors such differences both from a qualitative and a quantitative perspective. Some negative emissions solutions have momentum beyond the academic realm, with some of them, such as BECCS or Blue Carbon, being relatively popular in policy documents and media outlets. In addition, EW research has been discussed on social media such as Facebook. Second, very few options are linked to practical technological developments (i.e., mentions in patents), the only exception being DAC. Given the crucial role of the nexus between science, technology, and policy for developing specialized climate solutions, we investigate these three dimensions in greater detail in the next section.

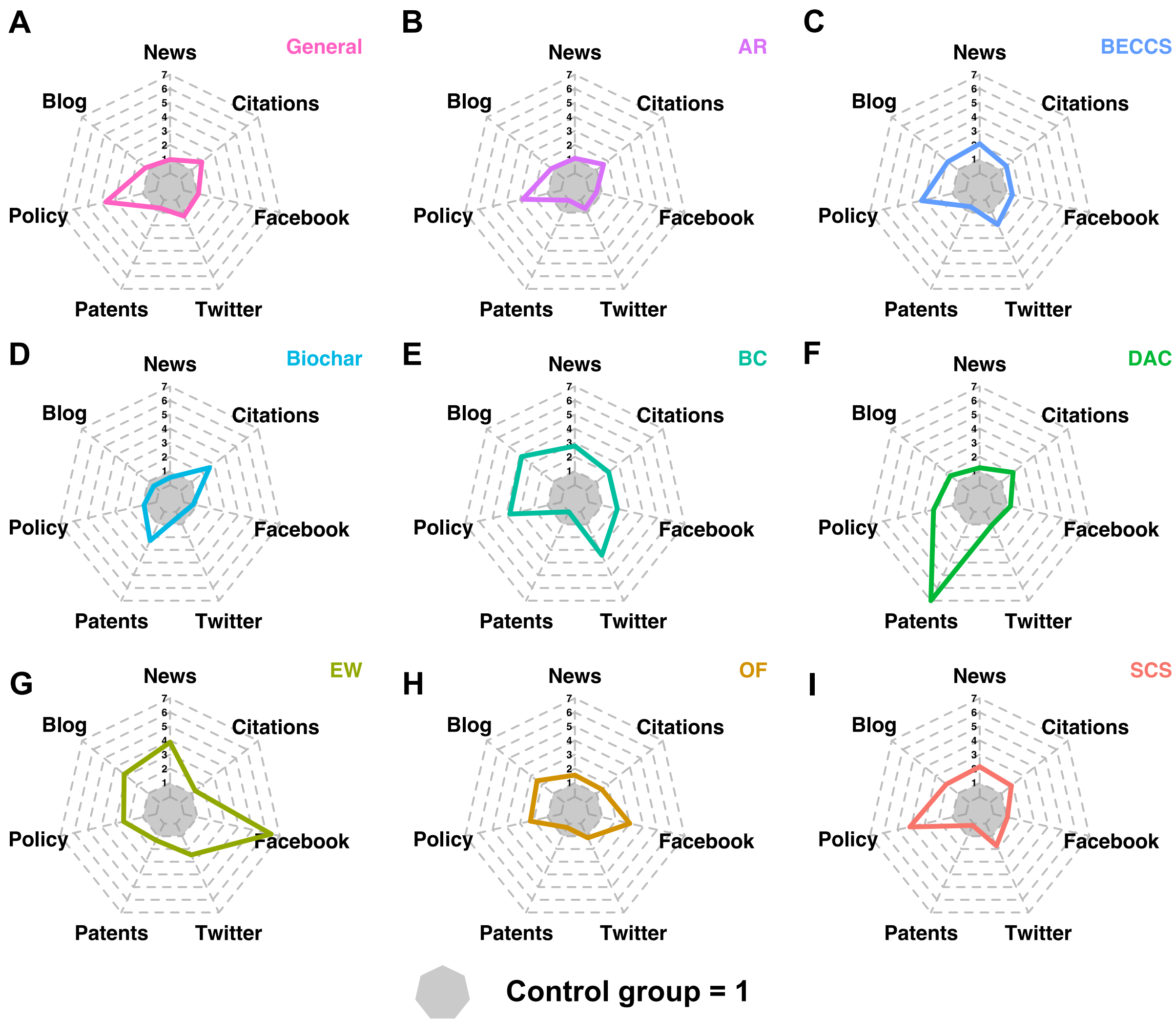

Figure 3: Multidimensional coverage of NETs research. **(A–I)** Radar charts for each NET, showing multidimensional spillovers (control group fixed at 1). **(A)** General. **(B)** Afforestation and reforestation – AR. **(C)** Bio-energy with Carbon Capture and Storage – BECCS. **(D)** Biochar. **(E)** Blue Carbon – BC. **(F)** Direct Air Capture – DAC. **(G)** Enhanced weathering – EW. **(H)** Ocean fertilization – OF. **(I)** Ocean fertilization – OF.

2.3 Quantifying knowledge flows to science, technology and policy

It has widely been argued that tackling climate change will require novel scientific research, practical technological innovations as well as policy support.[1] This section quantifies the impact that knowledge accumulation in NETs produces on technology, policy, and science itself.

We rely on econometric methods based on generalized linear models to estimate the size of knowledge spillovers. Our preferred specifications employ negative binomial regressions for citations counts and logistic regressions for citation likelihoods. We run a set of regressions on one-to-one matched samples to check the stability of our results and to quantify the uncertainty around our estimates (see section 4.2 and S2 for econometric and matching details). Results are summarized in Figure 4. In particular, Figure 4**A** highlights that several negative emissions options generate relative more spillovers than control groups. For instance, Biochar, BECCS and DAC articles collect, on average, 2.59, 1.84 and 1.83 times more citations than the non-NET control group, respectively. However, it is just for few NETs that scientific advances significantly impact on technological development (Figure 4**B**). Namely, DAC and Biochar research is somehow related to patenting activities, with a significant gap in favor of DAC. Indeed, DAC scientific advances are 7.89 times more likely to be cited by a patent. Contrarily, when looking at the probability of being cited by a policy document, BECCS and BC stand out among all the options (see Figure 4**C**).

To better quantify the variability of our point estimates as possible control groups vary, we compute the confidence interval around our mean effects size (i.e., β_k^*). Table 1 summarizes the mean effects for each coefficient across different runs of our statistical model (i.e., point estimates for all our NETs) and its variability. Our estimates prove relatively stable to possible differences in the matched control groups. Nevertheless, as far as scientific spillovers are concerned, we notice some differences between the baseline and climate control. As expected, climate change is a very active area of research, leading to smaller coefficients in our setting. In addition, we re-estimate our model including controls related to fields (or combination of fields) and whether articles are open access (see Figure S14 and S15). To further check the robustness of our results, we run our analysis using alternative control groups, different data sources, and alternative models (see section S6 for all the details). The insights of our empirical investigation are confirmed irrespective of specifications, data sources, and alternative measures. While there is plenty of evidence that citations, at least partially, capture positive knowledge spillovers for science and technology advances [44, 45], little is known about the references in policy documents. Hence, to better understand the role of citations coming from policy documents,

[1]See, for example, calls for attention by the EU Commission and the UK government.

we select a subset of policy reports to measure their overall sentiment. Our analysis shows that the overall sentiment of the documents citing NETs articles is positive (see section S3).

Our results already bring important implications for climate and innovation policy: NETs constitute an active research area with great potential and attract substantial attention within the scientific community. Nevertheless, our multidimensional spillovers estimates signal that most NETs hardly move beyond the scientific realm: only DAC research turns into marketplace innovations. In addition, the policy dimension seems to be relatively disconnected from the general scientific and technological trends. Finally, to better understand the trends that characterize NETs research efforts, we focus on the geography of NETs research and collaborations in the next section.

Table 1: Point estimates variability for baseline and climate control. IRRs and ORs (i.e. average exponentiated coefficients β_k^*) estimated through regression models – Eq. (1) – and relative variability of point estimates β_k [C.I. 95%].

	Baseline control			Climate control		
NET	Science	Technology	Policy	Science	Technology	Policy
General	1.71	0.75	2.88	1.40	0.99	1.93
	[1.55,1.88]	[0.720,0.77]	[2.81,2.94]	[1.39,1.42]	0.961,1.03]	[1.90,1.96]
AR	1.23	0.042	2.66	0.96	0.06	1.75
	[1.10,1.39]	[0.0412,0.04]	[2.61,2.72]	[0.95,0.97]	[0.0629,0.07]	[1.73,1.78]
BECCS	1.84	1.32	5.58	1.55	1.43	3.74
	[1.54,2.21]	[1.27,1.37]	[5.45,5.71]	[1.53,1.56]	[1.38,1.49]	[3.68,3.80]
Biochar	2.59	2.34	1.28	2.18	3.26	0.88
	[2.29,2.95]	[2.26,2.43]	[1.25,1.31]	[2.16,2.20]	[3.14,3.38]	[0.864,0.89]
BC	2.19	✗	4.67	1.78	✗	3.19
	[1.75,2.78]		[4.57,4.78]	[1.76,1.80]		[3.13,3.25]
DAC	1.83	7.89	2.08	1.82	12.3	1.47
	[1.54,2.19]	[7.59,8.19]	[2.04,2.13]	[1.17,1.20]	[11.9,12.8]	[1.44,1.49]
EW	1.46	2.50	4.27	1.19	4.02	2.50
	[1.11,1.97]	[2.41,2.59]	[4.13,4.40]	[1.17,1.20]	[3.85,4.18]	[2.46,2.53]
OF	0.896	0.401	2.27	0.70	1.03	1.34
	[0.702,1.16]	[0.39,0.42]	[2.21,2.33]	[0.69,0.71]	[1.00,1.06]	[1.31,1.37]
SCS	1.68	0.138	3.81	1.37	0.20	2.49
	[1.47,1.92]	[0.133,0.14]	[3.72,3.89]	[1.36,1.39]	[0.198,0.210]	[2.45,2.53]

Note: No valid estimates for BC in Technology due to absence of citations from patent documents.

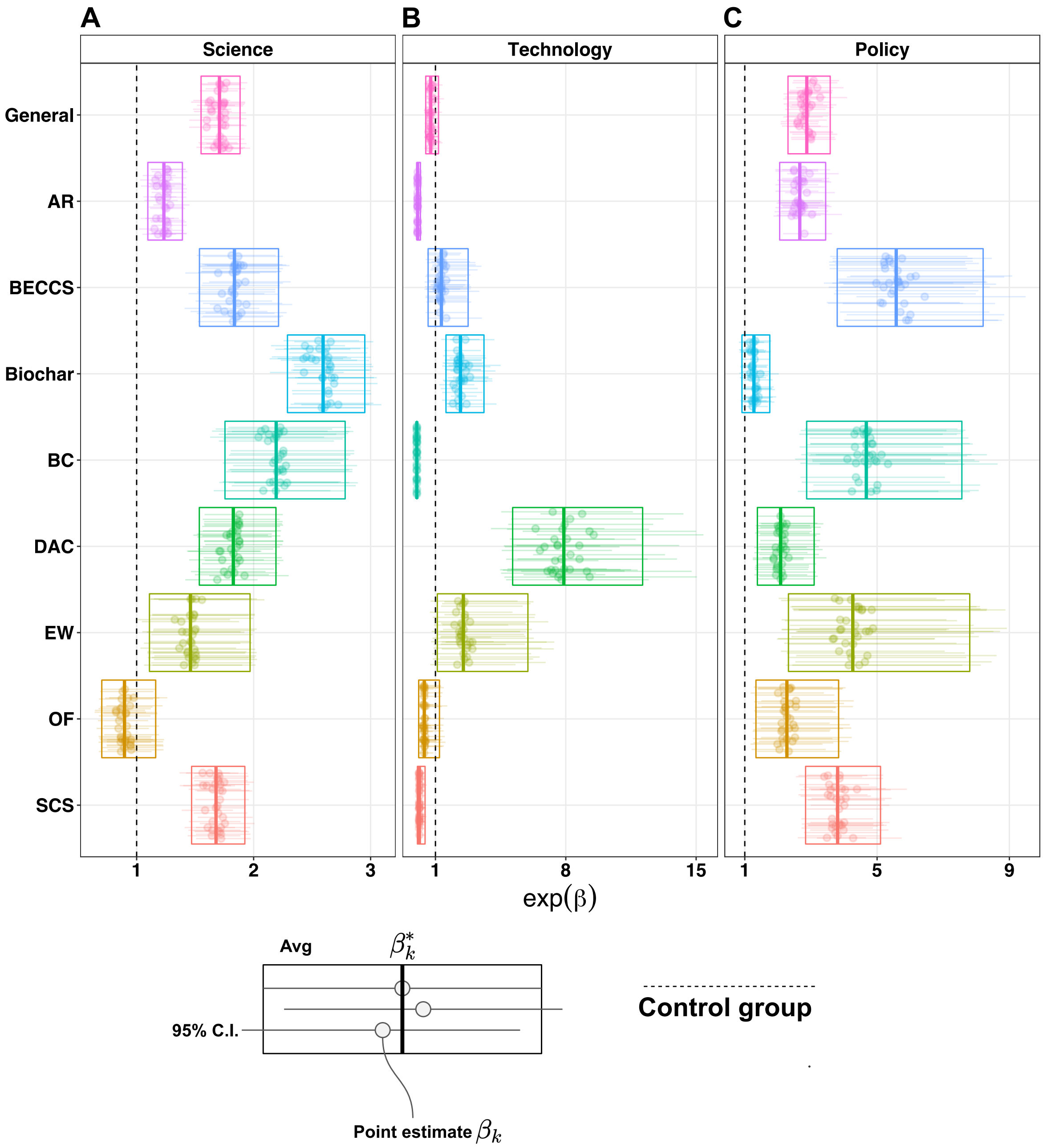

Figure 4: NETs spillovers to science, technology and policy. Coefficients (exponentiated) of the regression models of Eq. (1). Results are obtained by fitting 30 negative binomial regressions (**A**) and 30 logistic regressions (**B**–**C**) on one-to-one matched samples with year dummies. **(A)** Incident Rate Ratio (IRR) for each NET on the number of scientific citations. **(B)** Odds Ratio (OR) for each NET on the probability of being cited by a patent (BC estimates set to zero since there is no patent documents citing BC papers). **(C)** Odds Ratio (OR) for each NET on the probability of being cited by a policy document.

2.4 The geography of NETs research collaborations

So far, we have provided empirical evidence on the heterogeneity of NETs research in terms of knowledge base, scientific impact, and spillovers to practical applications.

Empirical evidence shows that proximity matters for complex activities and, more precisely, that innovation is disproportionately concentrated in cities [46, 47, 48]. So, in this section, we turn our attention to the geography of negative emissions research. First, we geo-localize NETs scientific articles using author affiliation data from WoS. Then, we derive countries' relative specializations by looking at the geographical distribution of research activities. Finally, we map scientific collaborations (at both the country and city level) to shed light on the identification of potential research hubs (see section 4.1 for more details on the geo-localization of NETs articles).

Figure 5**A** depicts the aggregate geographical distribution of research activities. The map shows the total number of articles related to NETs, the centrality (i.e., nodes' strengths) both at the city and country level and the overall collaboration network. For the sake of clarity, we filter out cities that appear less the ten times in our sample (see section 4.3 for network construction details). Beijing stands out as the city associated with the most significant number of articles and appears to be the most central city in the collaboration network. At the country level, though, the USA maintain their role as the primary research hub worldwide. However, the aggregate collaboration network can hardly allow us to dig deeper into a single technology, as it might be influenced by the distribution of articles across specific NETs. Therefore, we focus on different NETs separately. First, to better capture the relative specialization of countries in different NETs, we compute the Relative Scientific Advantage (RSA, see 4.3 for more details). Figure 5**B** summarizes the values of the RSA for a subset of countries, signaling, for instance, the greater specialization of European countries and the USA concerning engineering-based options such as BECCS and DAC. Intuitively, relative specializations still underline the links between research potentials and local opportunities. According to the RSA, Switzerland appears primarily specialized in DAC research, while Indonesia – one of the largest reserves of coastal forests – is almost fully specialized in BC. Next, we construct collaboration networks for all the NETs in our sample. Formally, we identify the largest connected component (i.e., the largest subset of nodes that can be reached from one another) and pin down the most central cities for each specific negative emissions option. As in Figure 2, we focus on AR, BECCS, DAC, and SCS (see section 4.3 for all NETs). Figure 5**C** points out that basic network measures can already allow us to spot different geographical specializations: Beijing and Canberra result as the most central locations as far as AR is concerned. Postdam and College Park are the most important hubs for BECCS research, while Fort Collins stands above in the SCS research.

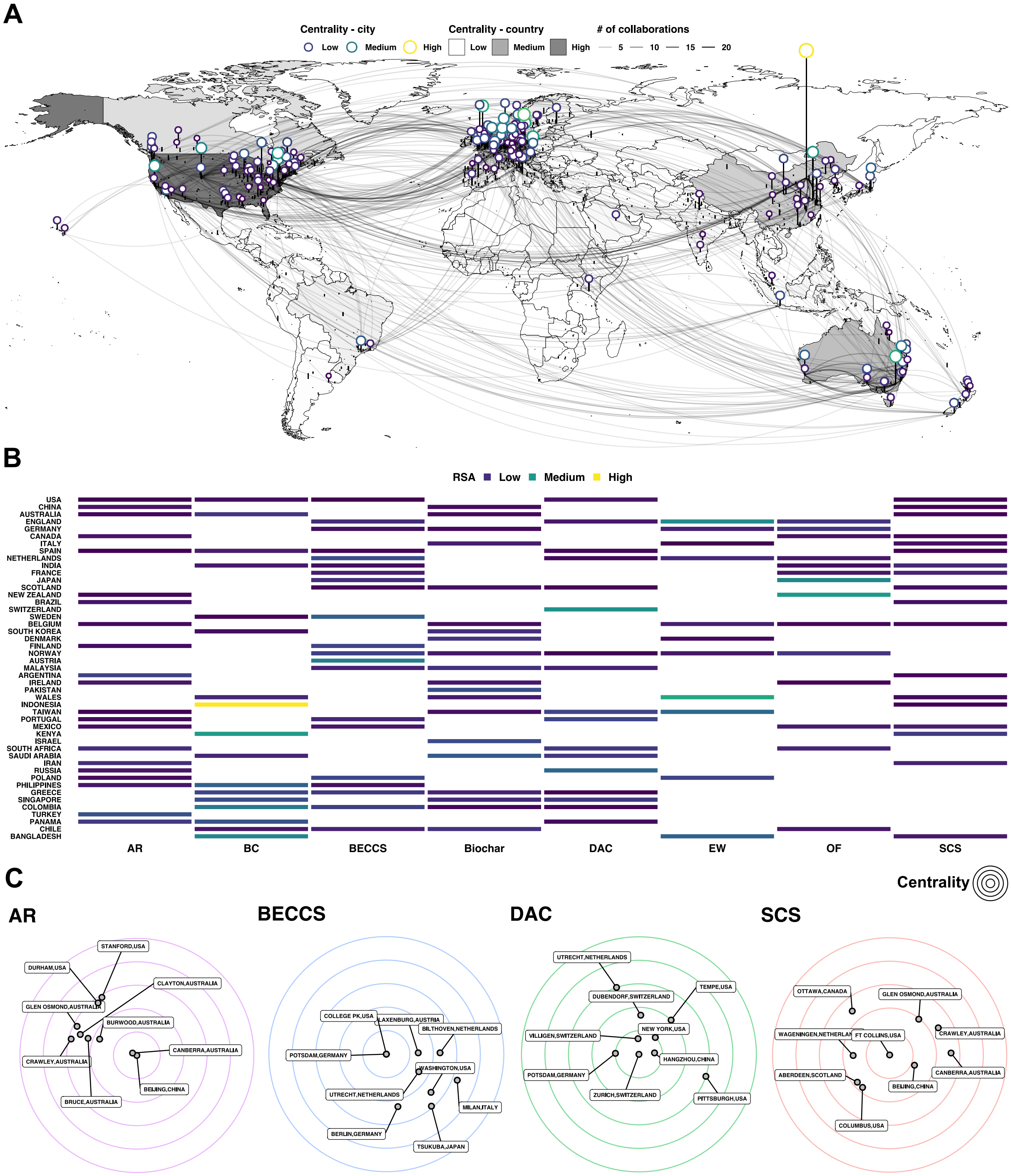

Figure 5: NETs geography and collaborations. **(A)** Geographical distribution of NETs research activities across cities (i.e., total number of NETs publications). Cities and countries centrality (i.e., node strength) scores are computed by analyzing the aggregate collaboration networks. **(B)** Revealed Scientific Advantage of selected countries (white spaces indicate values lower than 1). **(C)** Centrality ranking in the research collaboration networks related to AR, BECCS, DAC, and SCS.

Finally, Zurich appears as the most central city for DAC research. Interestingly, the company that first made it to the market with a commercial DAC solution was founded as spin-off of the ETH in Zurich (as of today, several companies are active in the DAC sector). The Zurich example highlights the importance of basic scientific research in developing technologically viable climate solutions and the role of geographical proximity between science and technology hubs. Innovative activities benefit from co-location, allowing scientists and inventors to form collaborations and share valuable knowledge. The potential research hubs identified above might well pave the way to accelerate advances in NETs.

3 Discussion

The urgent need for a rapid scale-up of NETs development and deployment should go hand in hand with extensive R&D efforts worldwide. Indeed, keeping track of the knowledge flows generated by negative emissions research would be crucial to inform scientists, market players, and policymakers on the potential opportunities for such technologies in the next few years. Our analysis provides a first quantitative comparison among different negative emissions solutions from the science-innovation nexus standpoint. Looking at knowledge spillovers within and outside the academic world, we find that negative emissions research is highly heterogeneous and spread across different hubs. Only a few options will eventually turn into marketplace inventions. As of today, DAC appears to be the most promising as far as practical technological innovations are concerned.

A quantitative benchmark of multidimensional spillovers for NETs can be considered as a starting point to evaluate the potential impact of NETs technological trajectories (or different climate-related technologies) from science to practical applications. In other words, it is an instrument that can be used by climate scientists and policymakers to keep track of scientific and technological trends from a systematic quantitative perspective.

Our empirical analysis is not without limitations, and some of these limitations point towards future research directions. First, the scientific literature on negative emissions is growing fast and in an interdisciplinary way. We follow a well-defined query strategy for the retrieval of data, relying on specific patterns and keywords. However, identifying the relevant articles and their disciplinary span might need more advanced criteria in the future. Machine learning/NLP models might prove helpful in finding better clusters of articles and consequently the direction of their spillovers. Second, we employ a matching procedure and propose an intrinsically stable resampling strategy to compare similar articles robustly. Nevertheless, we do not identify causal mechanisms or the impact of funding on the trajectories of such negative emission options. Relatively small advances might lead to sudden and sizeable changes for early-stage technologies. We can not rule out the possibility that some universally superior NET will appear in the following years or that some technological breakthroughs would make some existing ideas more likely to be patented. Finally, citations are only an imperfect measure of knowledge spillovers.

Although our methodology relies on different data sources, our quantification might still be subject to possible measurement errors.

From a policy perspective, our findings provide at least two clear insights. First, when considering the applicability of a diversified portfolio of NETs, their knowledge base, spillovers and trajectory of development should be considered carefully. Indeed, our analysis support evidence of little synergies between various NETs. Second, given the current distance of negative emissions research from the technological frontier, the prospective diffusion of NETs at scale would benefit from both conventional and unconventional innovation policies [49, 50, 51, 52]. In practice, R&D subsidies, public procurement, grants as well as the reinforcement of university-industry linkages could be coupled with the proposal of innovation prizes (e.g., XPRIZE) and Advance Market Commitments (AMC, e.g., Frontier), previously used to serve different scientific and policy purposes [53]. In addition, the evidence of strong positive knowledge spillovers could support a mission-oriented approach towards NETs [54]. Innovation can play an essential role in dealing with the climate change crisis [55]; however, science, technology, and policy need to be better coordinated to boost the efficacy of research endeavors.

4 Materials and methods

4.1 Data & matching

To track down the evolution of NETs research, we use three main sources of data: Web of Science (WoS), Reliance on Science (RoS), and Altmetric. WoS is a large global citations database collecting millions of research articles information and maintained by the private company Clarivate. RoS is a publicly available database that includes citations from patents to scientific articles [56]. Altmetric is a curated database that collects metrics complementary to standard citation-based data, such as mentions on a diverse set of outlets. Altmetric data can be freely available upon request for scientific purposes.

To identify the first sample of NETs relevant articles, we look at keywords, titles, and abstracts in WoS, as previously done in the literature [22, 23]. We retrieve a total of 3301 scientific articles from 1998 to 2017 for 8 different NETs. Note that the queries we used to filter DAC articles do not explicitly include storage (see S1), contrary to BECCS and in line with previous studies [22, 23]. All the articles that match the keywords search with no explicit reference in their titles or abstracts are included in the NET category *General* (see section S1 to find further descriptions of the sample and the full queries). Most of the articles retrieved from WoS are also covered in Altmetric ($\sim 62\%$). From WoS and Altmetric we can collect all cited and citing articles of our focal NETs sample. We use both RoS and Altmetric to recover patents-articles citation links, and Altmetric to keep track of all mentions from policy documents, mainstream media outlets as well as blogs and social media platforms such as Facebook or Twitter.

As far as the geo-localization of NETs scientific output is concerned, starting from authors' affiliation data, we use OpenStreetMap and the R package *tmap* to identify the coordinates of the cities linked to the publications in our sample. After a manual inspection, we can geo-localize a total of 3255 articles ($\sim 98\%$ of the initial set of articles).

To quantify multidimensional spillovers of NETs research, taking care of possible sources of bias, we employ an exact matching procedure and construct two controls groups: a "baseline" and a "climate" specific sample. First, for each focal negative emissions paper, we select up to 10 articles published in the same year and the same journal (the final pool of articles includes about $23k$ articles). Then, for our regression analysis, we further refine our procedure to match articles one-to-one. In detail, to check the stability of our results we create 30 sub-samples with replacement. We repeat the aforementioned procedure to construct a second set of control groups, specifically designed to match climate-change related articles. We retrieve climate-specific papers by querying WoS as in [57] (the final pool of climate-specific articles includes about $20k$ articles). Sections S2 and S1 describe in greater detail the matching scheme, the queries to collect the climate-specific control, and the overall compatibility among our different sources of data.

4.2 GLM regressions

To quantify knowledge spillovers in sections 2.3, we employ generalized linear regression models. After the construction of our one-to-one matched sub-samples, we estimate a negative binomial regression to model citation counts coming from scientific papers. Next, we use logistic regressions to model the probability of being cited by a patent or a policy document. The baseline specification can be written as follows:

$$g(E(S_{ikt}|NET_{ik}, T_{it}, \mathbf{X_i})) = \alpha + \sum_k \beta_k NET_{ik} + \sum_t \gamma_t T_{it} + \delta \mathbf{X_i} \tag{1}$$

where S_{ikt} is the number of forward citations (alternatively, the occurrence of a citation from a patent or a policy document), NET_{ik} refers to the corresponding technology and T_{it} represents a year dummy, and $\mathbf{X_i}$ a vector of control variables such as free accessibility of the articles or sub-fields categories (see section S6 for more details). Within this setting, the link function allows us to derive the relationship between the linear predictions and the expected value of the response variable (in our case a measure of knowledge spillovers). The link functions used for the binomial and negative binomial case are the following:

if $g(\cdot) = log\frac{\mu}{1-\mu}$ with $\mu = E(S_{ikt}|NET_{ik}, T_{it}) \rightarrow$ Logistic regression

if $g(\cdot) = log\mu$ with $\mu = E(S_{ikt}|NET_{ik}, T_{it}) \rightarrow$ Poisson/Negative Binomial regression

In practice, we estimate the models 30 times, to check the stability our results as the matched control groups vary. The boxes in figure 4 highlight the average effect: $\beta_k^* = \frac{1}{30}\sum_{c=1}^{30}\beta_{kc}$, where $c = \{1, \ldots, 30\}$ represent different matched control groups. The lower and upper bound of the boxes are instead the average confidence interval $\langle C.I.\rangle$, corresponding to the average value of the 95% confidence intervals across our estimates. In Table 1 we collect β_k and quantify the range of variation of these coefficients around their mean β_k^* (C.I. 95%).

4.3 Geographical specialization and collaboration networks

We employ the Revealed Scientific Advantage (RSA) to gauge countries' relative specialization. Such a metric was initially developed in [58] to analyze comparative international trade advantages among countries (i.e., Revealed Comparative Advantage – RCA). Later it has been extensively used in several applications beyond trade [59, 60]. Within our setting, for each country or location l and NET k, this is defined as

$$RSA_{lk} = \frac{\frac{w_{l,k}}{\sum_k w_{l,k}}}{\frac{\sum_l w_{l,k}}{\sum_{l,k} w_{l,k}}}, \tag{2}$$

where $w_{l,k}$ is the number of articles published in country l covering NET k. RSA values greater the 1 signal relative specialization.

By exploiting the geo-localization of NETs articles, we construct collaboration networks among cities to better understand where and how novel developments in negative emissions take place. The most straightforward way to analyze collaborations at different geographical levels is by using bipartite networks. A bipartite network is defined as a graph in which nodes are split into two separate sets (or layers). No link connects pairs of nodes that belong to the same layer. In our case, the two layers represent articles and cities, respectively. The binary case is simply described by a bi-adjacency matrix of dimensions $N_A \times N_C$. The number of rows N_A is the number of nodes in layer A (i.e., articles), and the number of columns N_C is the number of nodes in layer C (i.e., cities), as follows:

$$b_{ac} = \begin{cases} 1 & \text{if node } a \in \text{A and } c \in \text{C are linked} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

In this setting, we draw a link in the bipartite network if any of the authors of a NET research article a is affiliated with an institution of a given city c. A weighted monopartite projection on the article layer is constructed by counting the co-occurrences in the bipartite network and takes the form of a square $N_C \times N_C$ matrix $\mathbf{M}$ with elements:

$$m_{cc'} = \sum_{a=1}^{N_A} b_{ac} b_{a'c} \tag{4}$$

Before computing our centrality measures (i.e., nodes' strength), we first derive the largest connected component to filter out unconnected nodes (or groups of irrelevant nodes). Having information about cities, we can also derive the aggregate network at the country level. See section S7 for an additional description of our network analysis results.

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Supplementary Information

S1 Data

This work relies on three primary sources of data: Web of Science, Reliance on Science, and Altmetric. The identification of all NETs research articles follows a standard search strategy used in the literature [22, 23]. Using WoS, we retrieve 3301 articles for the time window 1998-2017. We consider eight different NETs, using keywords and patterns in titles and abstracts. The articles that match NETs keywords but do not include such words or patterns in titles or abstracts are listed in a residual category (i.e., General). The **query NETs WoS** in this section and Table S1 includes all the details and a brief summary description. Some articles might belong to more than one category. Accordingly, we count such articles in each potential category. For details, see the matrix of overlap in Figure S1. Working on quantifying knowledge spillovers, we are interested in keeping track of citation flows (in several dimensions). Therefore, we only include articles that received at least one academic citation for the analysis and for which the DOI was retrievable. Around 62% of the original WoS sample is also included in Altmetric (see Table S2 for a quick comparison, taking into account also the relative share of articles cited by patents or policy documents).

Query NETs WoS

(TS = (biochar* AND ((carbon OR CO2) NEAR/3 (sequest* OR storage OR stock OR accumulat* OR capture))) OR TS = (ocean NEAR/5 iron NEAR/5 (fertili*ation OR enrichment) NOT natural NOT ice* NOT glaci*) OR TS = ((soil NEAR/3 (carbon OR CO2) NEAR/3 (sequest* OR storage)) AND ("climate change" OR "global warm*") AND (manag* OR practice* OR restoration OR land-use)) OR TS = ((afforestation OR reforestation) AND ((carbon OR CO2) NEAR/3 (sequest* OR storage))) OR (TS = (("ocean liming") AND (removal OR storage) AND (CO2 OR carbon*)) OR TS = ((geoengineer*) AND (silicate OR olivine OR albite OR CACO3)) OR TS = ((silicate OR olivine OR albite OR CACO) AND (mitigat* NEAR/3 ("climate change" OR "global warming"))) OR TS = (("ocean alkalini*") AND (remov* OR storage OR mitigat* OR sequest*) AND (CO2 OR carbon*)) OR TS = (((enhance* OR artificial*) NEAR/2 weathering) AND ((carbon OR CO2 OR "climate change" OR "global warming") NEAR/3 (remov* OR sequest* OR storage OR sink OR mitigat* OR reduc*)))) NOT TS = (glaci* OR ice* OR ordovic* OR Aptian OR Cenozo* OR Paleo* OR Mezoso*) OR (TS = (((capture OR extraction OR absorbtion) NEAR/3 (air OR atmosph*)) AND (ambient OR "atmosph* pressure*") AND (CO2 OR carbon)) OR TS = (((captur* OR extract) NEAR/3 (direct* OR "carbon dioxide") NEAR/3 (air OR atmosph*)) AND (CO2 OR carbon)) OR TS = ((*sorbent OR amine) AND capture AND (carbon OR CO2) AND ("ambient air")) OR TS = ((captur* NEAR/3 CO2 NEAR/3 (air OR atmosph*)) AND solar)) NOT TS = (phenolic OR PCB* OR particulate OR NOx OR isotope OR "heat pump" OR polycyclic OR *bacteria* OR lignin OR sink OR pollution OR photosynth* OR biofuel* OR sugar) OR TS = (BECCS OR ((biomass OR bioenerg*) AND ("CCS" OR "Carbon capture and Storage" OR "Carbon dioxide capture and Storage" OR "CO2 capture and storage")) NOT "co-fir*" NOT "co-generat*" NOT cogeneration NOT coal) OR TS = ((seagrass OR mangrove* OR macroalgae OR "blue carbon") AND ((carbon OR CO2) NEAR/3 (sequest* OR accumulat* OR storage OR capture)) AND (deforest* OR afforest* OR conserv* OR restor* OR manag*)) OR (TS = ((CDR AND (CO2 OR carbon*)) OR "negative carbon dioxide emission*" OR "negative CO2 emission*" OR "negative GHG emission*" OR "negative greenhouse gas emission*" OR "carbon-negative emission*" OR ("negative emission*" NEAR/10 carbon) OR ("negative emission*" NEAR/10 CO2)) OR TS = (geoengineering AND ((carbon OR CO2) NEAR/3 (sequest* OR accumulat* OR storage OR capture))) OR TS = (("geoengineering" OR "climate engineering") AND CDR)) NOT TS = (N2O OR nitrogen OR NOX)) NOT TS = ("bioactive equivalent combinatorial components" OR "bandwidth-efficient-channel-coding-scheme" OR "bronchial epithelial cell cultures" OR "california current system" OR comet OR mars OR exoplanet* OR "competition chambers" OR gastric OR (mercury NEAR/3 capture) OR (image NEAR/3 capture) OR "canary current system" OR "heavy metal" OR eicosanoid OR "companion cells" OR "calcium carbonate sand" OR "copper chaperone" OR "commercial cane sugar" OR "Cindoxin reductase" OR "coupled dissolution reprecipitation" OR "carbon dioxide reforming" OR rats OR "complementarity determining regions" OR deoxycytidine)

Table S1: Data description

NET	Code	Description	N	%
Afforestation/Reforestantion	AR	Forest management and restoration programs increase the CO2 captured from the atmosphere and stored in living biomass.	677 (603)	21 (21)
Bio-energy with Cabon Capture and Storage	BECCS	Biomass is grown and used to power as a source of thermal energy. The CO2 produced is captured and stored in geological reservoirs.	247 (206)	7 (7)
Biochar	Biochar	The pyrolysis of biomass produce charcoal (i.e., biochar). It can be used as soil additive, with positive effect in terms of carbon capture and stored in soil.	555 (478)	17 (17)
Blue Carbon	BC	Blue carbon refers to carbon captured by the world's ocean and coastal ecosystems, such as sea grasses, mangroves, or salt marshes.	121 (96)	4 (3)
Direct Air Capture	DAC	CO2 is absorbed directly from the atmosphere through chemicals and stored.	245 (214)	7 (8)
Enhanced Weathering	EW	Minerals that can absorb CO2 are grinded and spread in lands or oceans.	71 (63)	2 (2)
Ocean Fertilization	OF	Nutrients (such as iron) can stimulate the growth of phytoplankton. Consequently, the absorbed CO2 is naturally sequestered in the ocean.	113 (102)	3 (4)
Soil Carbon Sequestration	SCS	More efficient agricultural practices enhance soils carbon absorption potential.	410 (354)	12 (12)
General	General	NETs scientific articles with no specific keywords in titles or abstract.	1059 (906)	
Total (with citation info WoS)		The total only includes unique articles (they might belong to more than one category).	3301 (2850)	

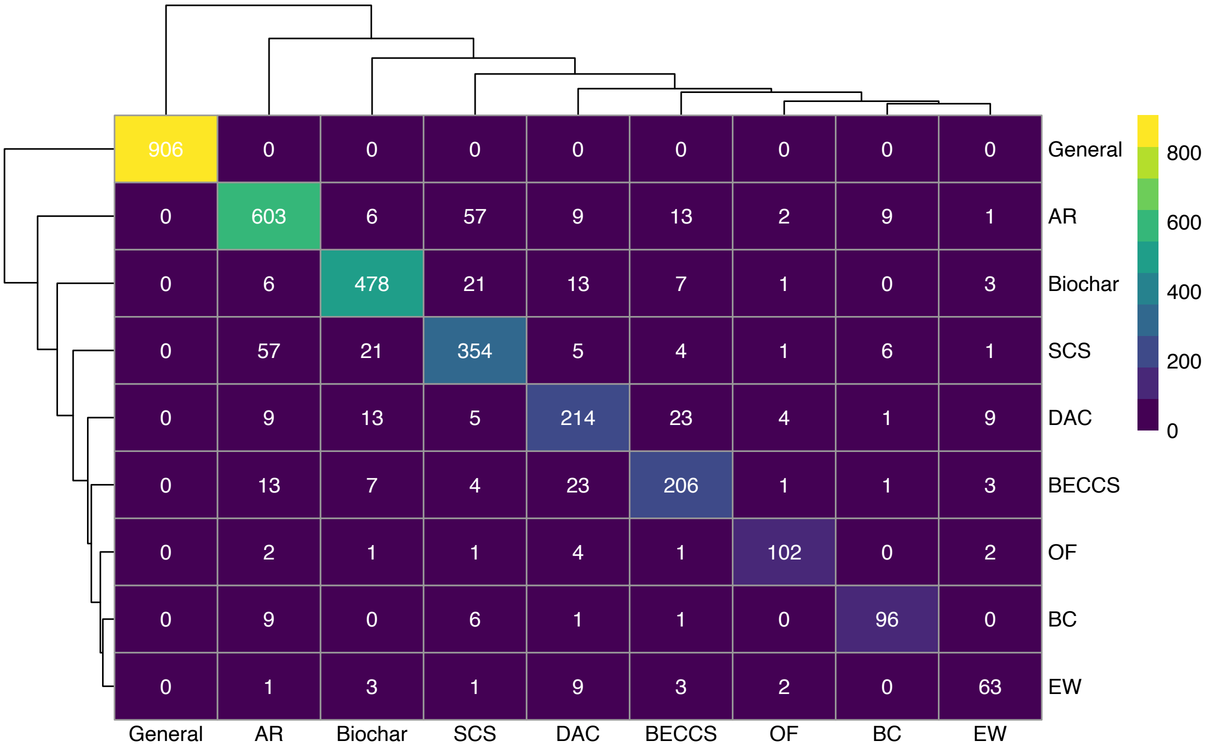

Figure S1: NETs overlap in articles. Each entry of the matrix shows the number of articles including more than one NET category. Along the diagonal the total sum for every NET.

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Table S2: Share of NETs articles linked to technology and policy – Altmetric vs. (WoS–RoS)

NET	N	% with policy citation	% with patent citation
General	556 (906)	39	3 (3)
AR	354 (603)	43	0.2 (1)
BECCS	135 (206)	49	5 (3)
Biochar	293 (478)	20	8 (9)
BC	78 (96)	44	0 (0)
DAC	143 (214)	32	27 (23)
EW	54 (63)	44	11 (9)
OF	78 (102)	42	3 (8)
SCS	247 (354)	47	0.8 (2)

The total number of articles retrieved via Altmetric is 2040. The number of articles for which we have both WoS and Altmentic data, coupled with citations data and DOI information in both dataset is 1800. Articles might belong to more than one NET category as shown in S1. The information collected through Reliance in Science (RoS) allow us to compare the coverage in terms of patent citations for a larger sub-sample.

S2 Matching

Our empirical analysis relies on quantitative comparisons. Therefore, we rely on a matching strategy to avoid reaching misleading interpretations based on potentially biased estimates. The first step of our matching scheme is to construct a control group by collecting – through WoS – up to 10 articles (with replacement) published in the same year and the same journal. Consequently, we obtain up to 10 twin articles for each NETs paper of interest. As far as the regression analyses are concerned, we further enhance our matching strategy. In practice, we generate 30 one-to-one matched sub-samples (without replacement) to control our estimates' stability. Figure S2 depicts the steps of our matching scheme. Furthermore, we use the same strategy to construct a second set of control groups specifically linked to the climate-related literature. We retrieve climate-specific articles following the **Query climate control WoS** (listed below and already validated in the literature [57]). Finally, Figure S3 shows a treemap of the most popular venues that publish NETs articles. We list venues that appear at least 10 times in our sample.

Query climate control WoS

SO=(Climate Alert OR Climate Dynamics OR Climate Policy OR Climatic Change OR Global and Planetary Change OR Global Change Biology OR International Journal of Greenhouse Gas Control OR Mitigation and Adaptation Strategies for Global Change) OR TS=(((CO2 OR "carbon dioxide" OR methane OR CH4 OR "carbon cycle" OR "carbon cycles" OR "carbon cycling" OR "carbon budget*" OR "carbon flux*" OR "carbon mitigation") AND (climat*)) OR (("carbon cycle" OR "carbon cycles" OR "carbon cycling" OR "carbon budget*" OR "carbon flux*" OR "carbon mitigation") AND (atmospher*))) OR TS=("carbon emission*" OR "sequestration of carbon" OR "sequester* carbon" OR "sequestration of CO2" OR "sequester* CO2" OR "carbon tax*" OR "CO2 abatement" OR "CO2 capture" OR "CO2 storage" OR "CO2 sequester*" OR "CO2 sequestration" OR "CO2 sink*" OR "anthropogenic carbon" OR "captur* of carbon dioxide" OR "captur* of CO2" OR "climat* variability" OR "climat* dynamic*" OR "chang* in climat*" OR "climat* proxies" OR "climat* proxy" OR "climat* sensitivity" OR "climat* shift*" OR "coupled ocean-climat*" OR "early climat*" OR "future climat*" OR "past climat*" OR "shift* climat*" OR "shift in climat*") OR TS=("atmospheric carbon dioxide" OR "atmospheric CH4" OR "atmospheric CO2" OR "atmospheric methane" OR "atmospheric N2O" OR "atmospheric nitrous oxide" OR "carbon dioxide emission*" OR "carbon sink*" OR "CH4 emission*" OR "climat* policies" OR "climat* policy" OR "CO2 emission*" OR dendroclimatolog* OR ("emission* of carbon dioxide" NOT nanotube*) OR "emission* of CH4" OR "emission* of CO2" OR "emission* of methane" OR "emission* of N2O" OR "emission* of nitrous oxide" OR "historical climat*" OR IPCC OR "methane emission*" OR "N2O emission*" OR "nitrous oxide emission*") OR TS=("climat* change*" OR "global warming" OR "greenhouse effect" OR "greenhouse gas*" OR "Kyoto Protocol" OR "warming climat*" OR "cap and trade" OR "carbon capture" OR "carbon footprint*" OR "carbon neutral" OR "carbon offset" OR "carbon sequestration" OR "carbon storage" OR "carbon trad*" OR "changing climat*" OR "climat* warming")

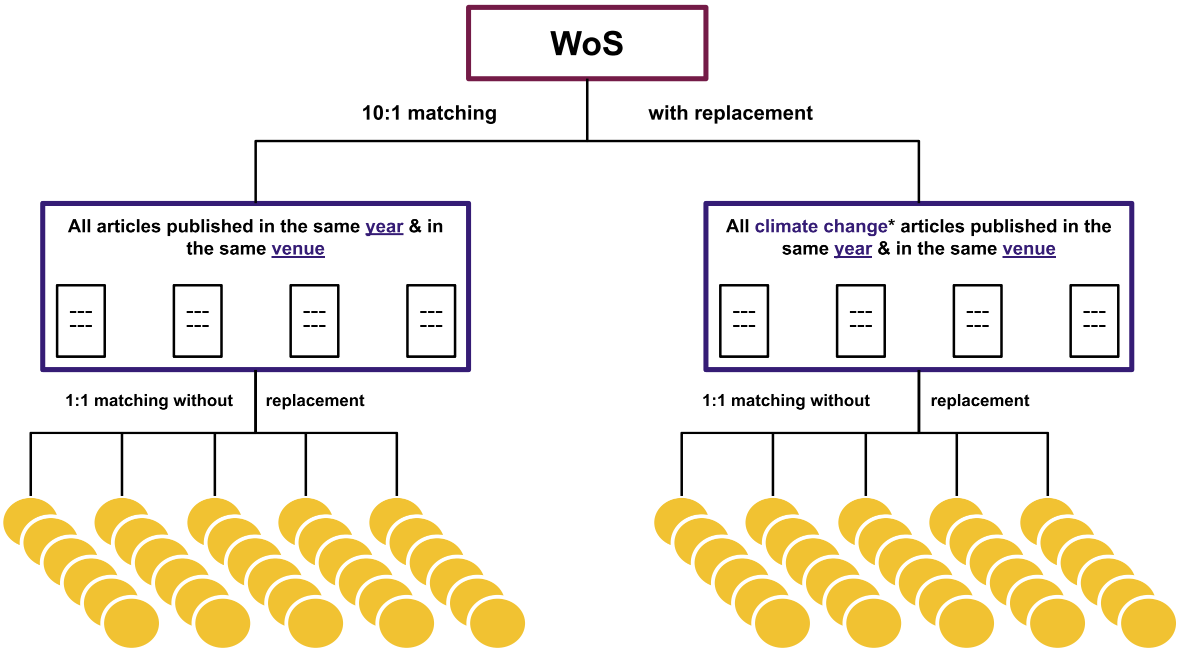

Figure S2: Matching scheme. A schematic representation of the matching procedure used in the empirical analysis. The right end side refer to the construction of the baseline control group; while the left end side refers to the climate control.

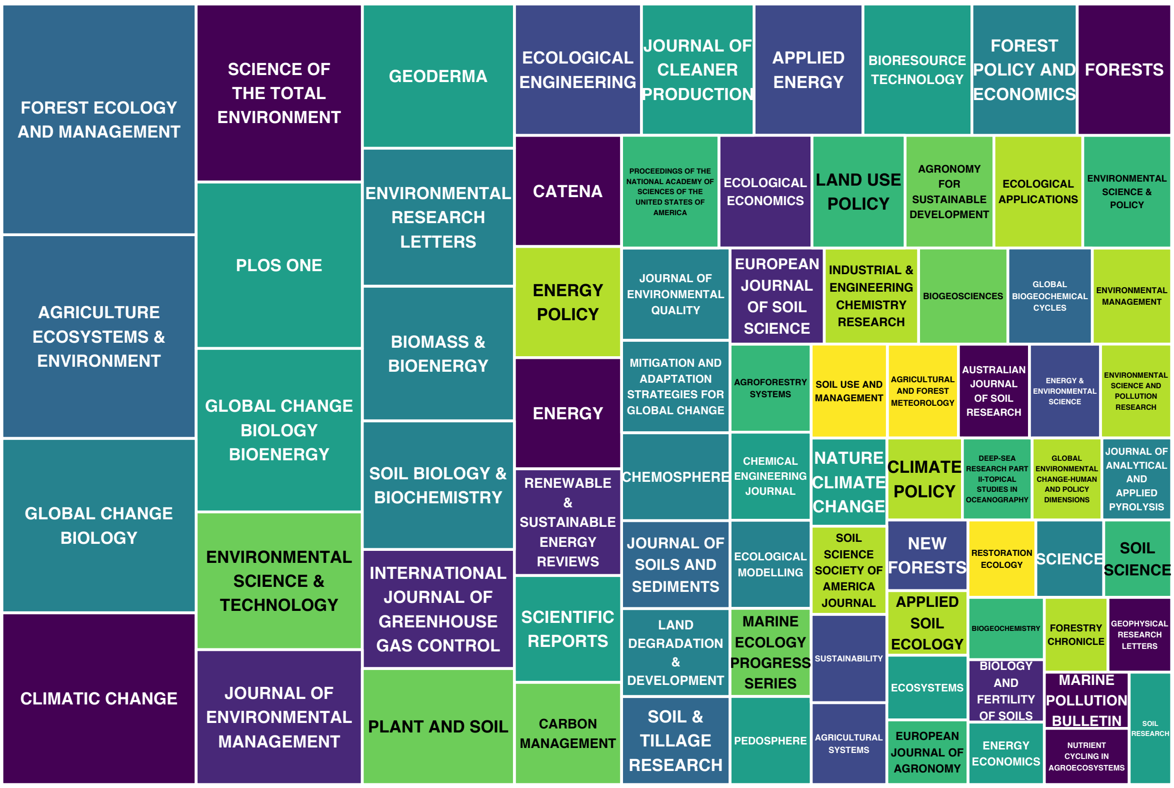

Figure S3: Top NETs Venues. Treemap listing the most representative venues for NETs articles. The map include academic journals that published at least 10 paper related to NETs.

S3 Policy sentiment analysis

Citations coming from policy documents are collected through Altmetric (see section 4.1. While academic and patent citations have historically been used to keep track of knowledge flows [44, 32], there is little evidence that policy citations capture positive mentions for scientific results.

To partly tackle this issue, we explore the sentiment of a subset of policy documents that cite our focal articles. First, we select 208 (English) documents and then analyze their entire text using NLP methods. Although working on the entire text is subject to potential measurement errors, the overall sentiment ratio of each document gives us a first indication of the orientation. We define the sentiment ratio by simply counting the number of positive words over the total number of words (see Figure S4).

To derive our measure, we use a dictionary-based approach, that is, a list of general-purpose lexicons collected for text analysis studies and freely available through the R package *tidytext* [61].

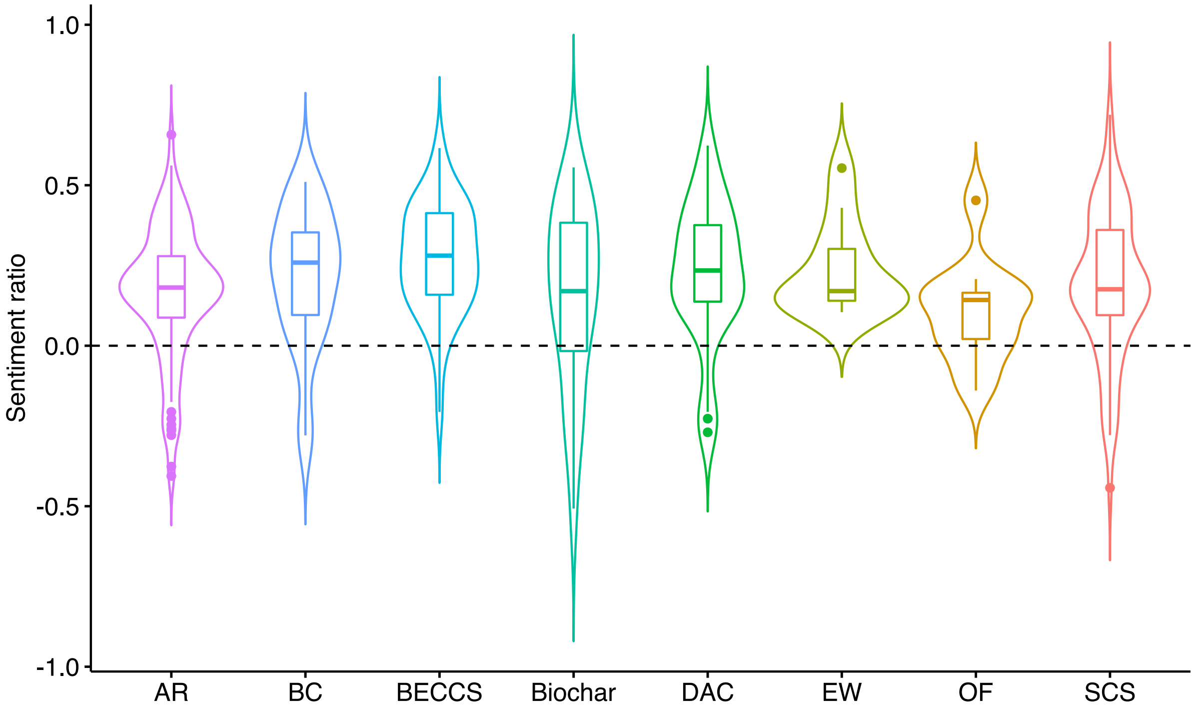

Figure S4: Sentiment of policy documents. Violin plots showing the sentiment ratio of policy documents citing scientific articles related to NETs.

S4 Knowledge flows

As mentioned in section 3, we collect all backward and forward citations (through WoS) for all the NETs articles in our sample. The purpose is to identify the knowledge base and the potential direction of scientific spillovers. The flow diagrams depicted in Figure S5 highlight the differences between nature-based and technology-based negative emissions options. We consider the 10 largest sub-fields to clarify the scientific linkages concerning different NETs better. The 10 most important fields account for more than 75% of the total citations. Figure S6 shows the exact distribution for all our NETs options. To summarize the main trends: forestry, ecology, and soil science dominate in the nature-based NETs, while advances in chemistry and chemical engineering shape DAC and BECCS developments. EW and Biochar can be placed between these two groups, sharing some nature-based knowledge components and technical features. Not surprisingly, OF and BC disproportionally link to oceanography and marine biology.

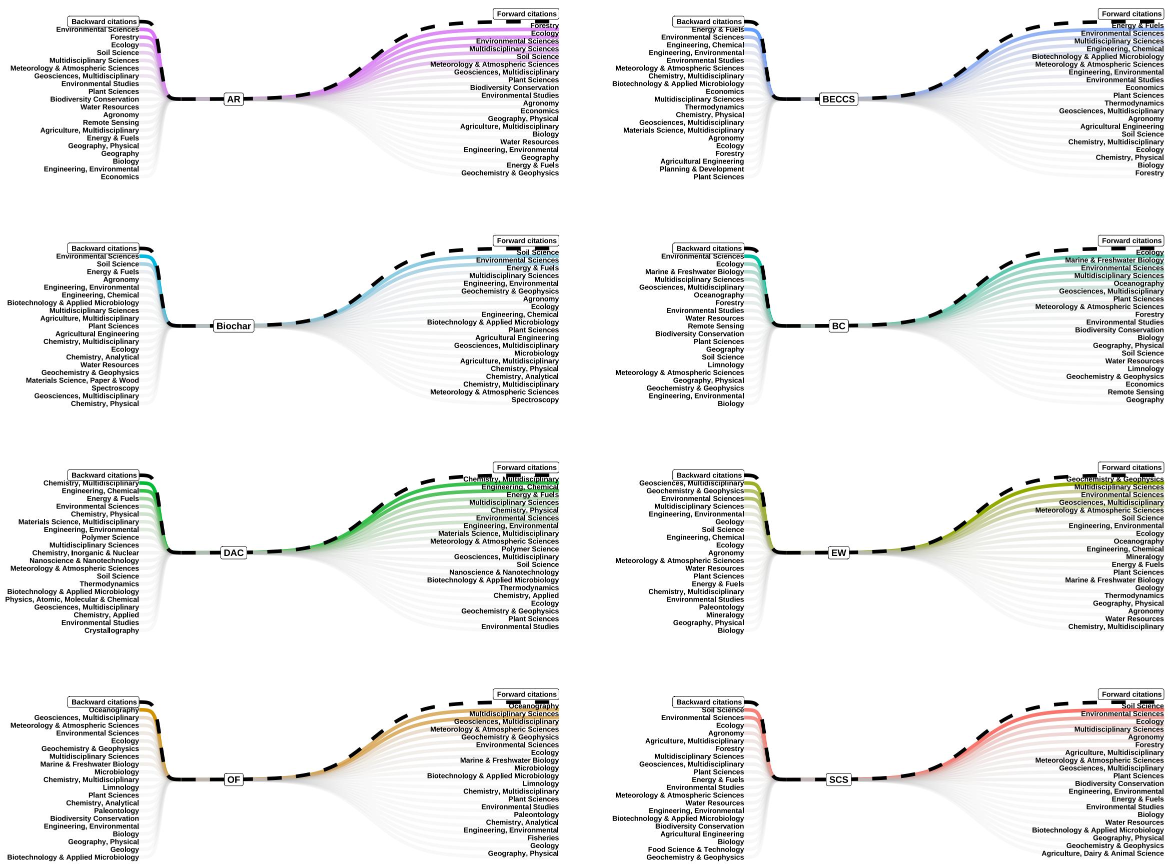

Figure S5: Knowledge flows. Top 10 WoS subjects that affect (backward citations) and are affected (forward citations) by NETs research. **(AR)** Afforestation and Reforestation. **(BECCS)** Bio-energy with Carbon Capture ans Storage. **(Biochar)** Biochar. **(BC)** Blue Carbon. **(DAC)** Direct Air Capture. **(EW)** Enhanced Weathering. **(OF)** Ocean Fertilization. **(SCS)** Soil Carbon Sequestration.

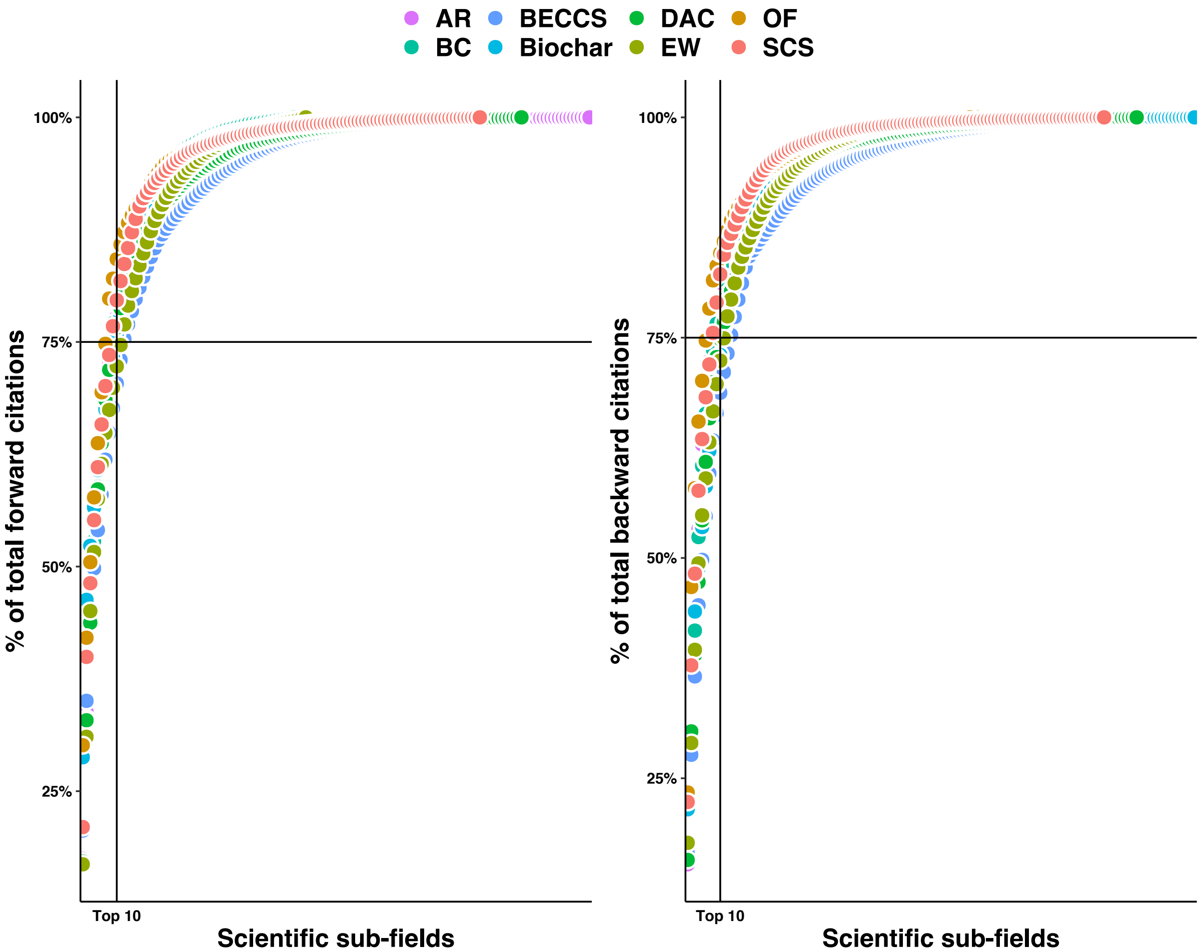

Figure S6: Pareto plot. Cumulative percentage of the total number of forward and backward scientific citations by NETs. The horizontal reference line marks the 75% of total citations. The vertical reference line indicates the 10 largest scientific sub-fields.

S5 Radar - climate control

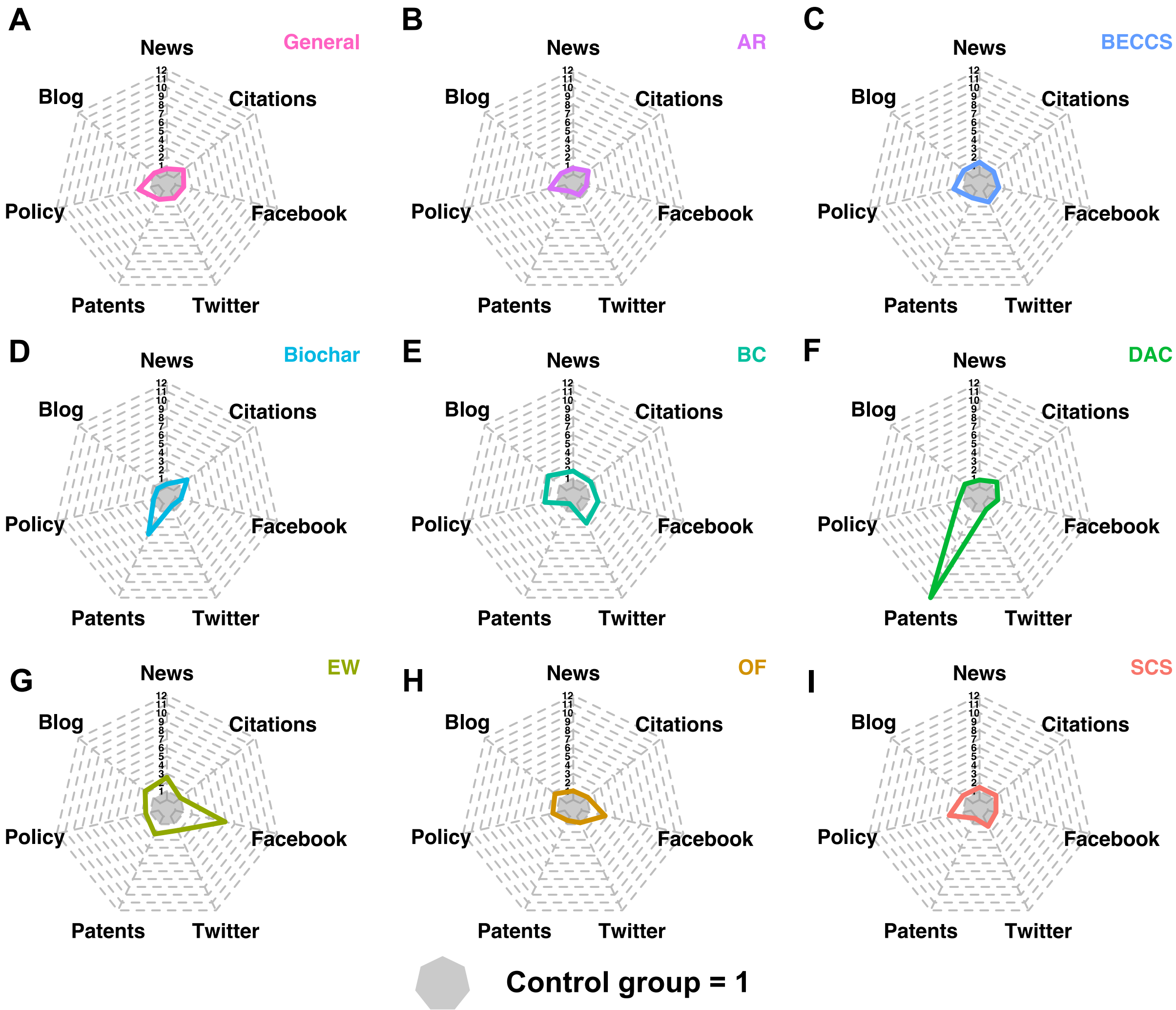

Figure S7: NETs multidimensional impact – Climate control (A–I) Radar charts for each NET, showing multidimensional spillovers (*climate* control group fixed at 1). **(A)** General. **(B)** Afforestation and reforestation – AR. **(C)** Bio–energy with Carbon Capture and Storage – BECCS. **(D)** Biochar. **(E)** Blue Carbon – BC. **(F)** Direct Air Capture – DAC. **(G)** Enhanced weathering – EW. **(H)** Ocean fertilization – OF. **(I)** Ocean fertilization – OF.

S6 Regressions - Robustness

We perform a long series of robustness checks to validate our results. First, as mentioned in section 4.2, we estimate our baseline models 30 times, with varying control groups. The boxes depicted in Figure 4 show the average point estimate β^*_k and the average confidence intervals $\langle C.I. \rangle$ across the 30 runs of our statistical model (see Table S3 for more details). Second, we run the analysis using different control groups, focusing, for instance, on the climate change literature (Section S2 covers details on the construction of the climate control). Figure S4 and Table S4 summarize the result of our analysis with the climate control groups as reference.

In addition, we repeat our analysis using a linear model instead of GLMs. Formally, we used the following specification:

$$log(S_{ikt}) = \alpha + \sum_k \beta_k NET_{ik} + \sum_t \gamma_t T_{it} + \epsilon \tag{5}$$

where S_{ikt} is the number of forward citations in the science, technology, or policy dimension, NET_{ik} refers to the corresponding NET and T_{it} represent a year dummy, as in Section 2.3. Results are summarized in Figure S9 and Table S5 with the baseline control, and in Figure S15 and Table S6 with the climate control.

To further evaluate the consistency of our results and control for potential differences in coverage between WoS and Altmetric, we repeat the analysis, comparing the quantitative trends highlighted so far in terms of scientific and technological spillovers. Following the empirical strategy of Section 2.3, we first use WoS – instead of Altmetric – to quantify scientific spillovers, namely: citations and scope (i.e., # of different fields that cite a given article). Figure S11,S12 and Table S7, S12 summarize the results concerning both the baseline and the climate control groups. Then, we also use RoS to keep track of the science-technology links. We repeat the analysis using logistic regressions as in Section 2.3. Figure S13 and Table S9 confirm the overall distance of NETs from the technological frontier, and the relative advantage of DAC. We also perform an additional robustness check by estimating the models of Section 2.3 including two potentially relevant control variables: a field (or combinations of fields) indicator extracted via Altmetric and whether the article is open access. A categorical field variable (F_{if}) allows us to control for disciplinary differences in citation patterns within and beyond science. A dummy that captures whether articles are open access (OA_i) controls for the possibility of broader/more accessible diffusion of knowledge.

More formally, we employ the following specification:

Table S3: Coefficients and C.I. Figure 4

	Science		Technology		Policy	
NET	$\exp\beta$	$\langle C.I.\rangle$	$\exp\beta$	$\langle C.I.\rangle$	$\exp\beta$	$\langle C.I.\rangle$
General	1.68	[1.53,1.86]	0.70	[0.45,1.1]	2.85	[2.26,3.58]
AR	1.25	[1.11,1.41]	0.04	[0.01,0.18]	2.66	[2.03,3.47]
BECCS	1.88	[1.58,2.27]	1.29	[0.6,2.66]	5.65	[3.8,8.41]
Biochar	2.61	[2.3,2.97]	2.29	[1.48,3.53]	1.31	[0.93,1.82]
BC	1.88	[1.5,2.39]	✗		4.36	[2.62,7.18]
DAC	1.86	[1.57,2.23]	7.48	[5,11.34]	2.06	[1.36,3.09]
EW	1.39	[1.05,1.88]	2.47	[1.03,5.63]	4.70	[2.49,8.87]
OF	0.92	[0.72,1.21]	0.39	[0.09,1.32]	2.31	[1.32,4.01]
SCS	1.63	[1.43,1.88]	0.14	[0.03,0.44]	3.75	[2.76,5.1]
Year dummies	✓		✓		✓	
Matched samples	30		30		30	
# of obs.	3392		3392		3392	

$$g(E(S_{ikt}|\dots)) = \alpha + \sum_k \beta_k NET_{ik} + \sum_t \gamma_t T_{it} + \sum_f \delta_f F_{if} + \mu OA_i \quad (6)$$

Figure S14,S15 and Table S10,S11 include all details. Some coefficients shirk vis-a-vis our baseline model of section 2.3, as the field control is sufficiently strong to clean out the disciplinary heterogeneity that distinguishes, for instance, engineering-based articles from marine biology or generally less cited sub-fields.

Lastly, we finally check the robustness of our results by running individual regressions for some NETs with NET-specific control groups. In detail, Figure S16 show the estimates for AR, BECCS, DAC, and SCS. The outcomes confirm that only DAC has a significant association with technological developments. Overall, the many specifications we have explored corroborate our main results, with coefficients' values ranging across specific specifications and control groups.

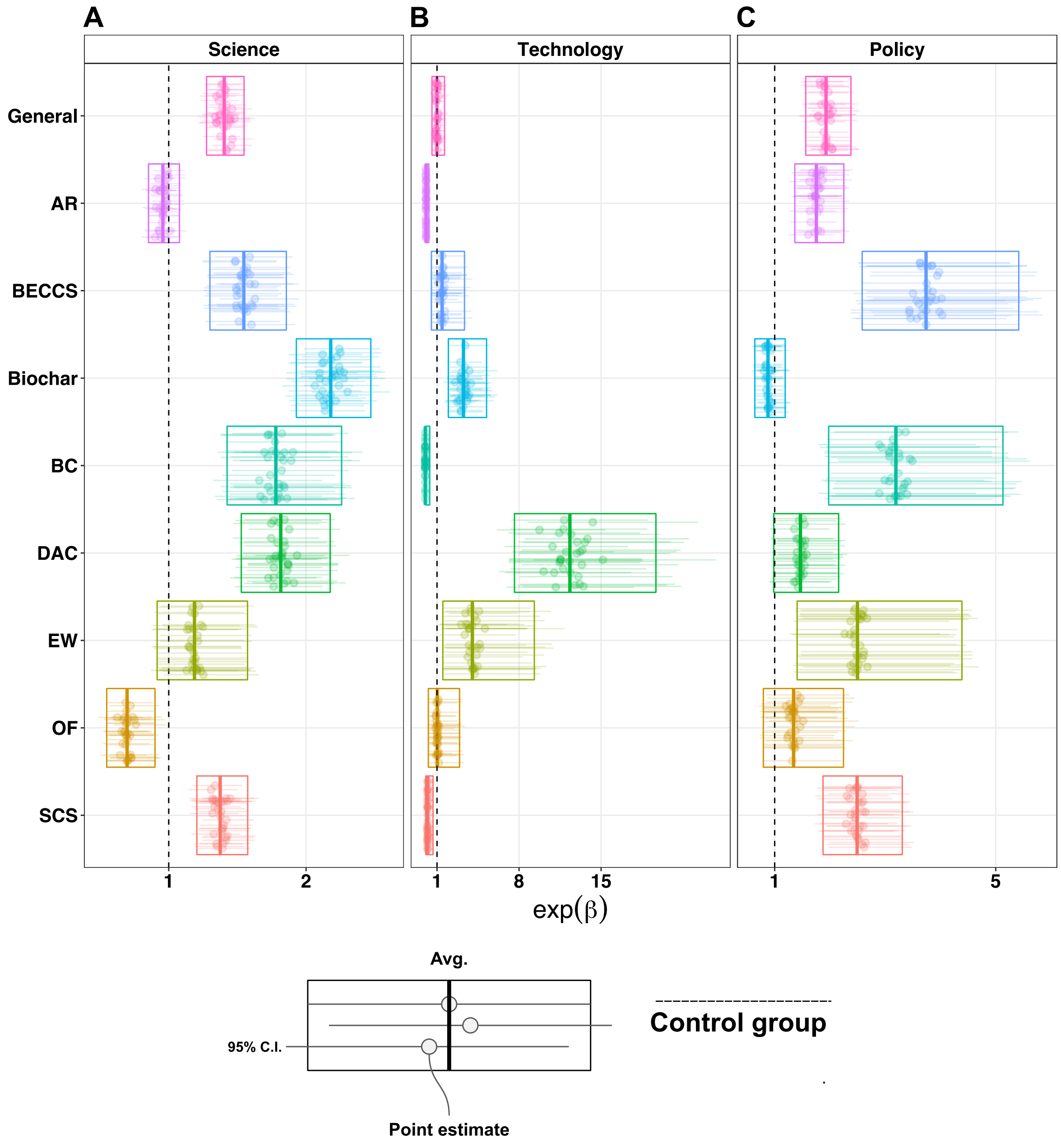

Figure S8: NETs spillovers to science, technology and policy (climate). Coefficients of the regression models of Eq. (3). Results are obtained by fitting 30 negative binomial regressions (**A**) and 30 logistic regressions (**B**–**C**) on one-to-one matched samples with year dummies. **(A)** Estimated coefficients (exponentiated) for each NET on the number of scientific citations. **(B)** Estimated coefficients (exponentiated) for each NET on the probability of being cited by a patent (BC estimates set to zero since there is no patent documents citing BC papers). **(C)** Estimated coefficients (exponentiated) for each NET on the probability of being cited by a policy document.

Table S4: **Coefficients and C.I. Figure S8**

NET	Science		Technology		Policy	
	$\exp\beta$	$\langle C.I. \rangle$	$\exp\beta$	$\langle C.I. \rangle$	$\exp\beta$	$\langle C.I. \rangle$
General	1.40	[1.28,1.55]	0.99	[0.57,1.64]	1.93	[1.56,2.38]
AR	0.96	[0.85,1.08]	0.06	[0,0.3]	1.75	[1.36,2.25]
BECCS	1.55	[1.3,1.86]	1.43	[0.52,3.34]	3.74	[2.58,5.42]
Biochar	2.18	[1.93,2.47]	3.26	[1.97,5.23]	0.88	[0.64,1.19]
BC	1.78	[1.42,2.26]	✗		3.19	[1.98,5.13]
DAC	1.82	[1.53,2.18]	12.34	[7.61,19.68]	1.47	[0.98,2.16]
EW	1.19	[0.92,1.57]	4.02	[1.5,9.3]	2.50	[1.41,4.39]
OF	0.70	[0.55,0.9]	1.03	[0.26,2.92]	1.34	[0.79,2.25]
SCS	1.37	[1.2,1.58]	0.20	[0.04,0.66]	2.49	[1.87,3.31]
Year dummies	✓		✓		✓	
Matched samples	30		30		30	
# of obs.	3716		3716		3716	

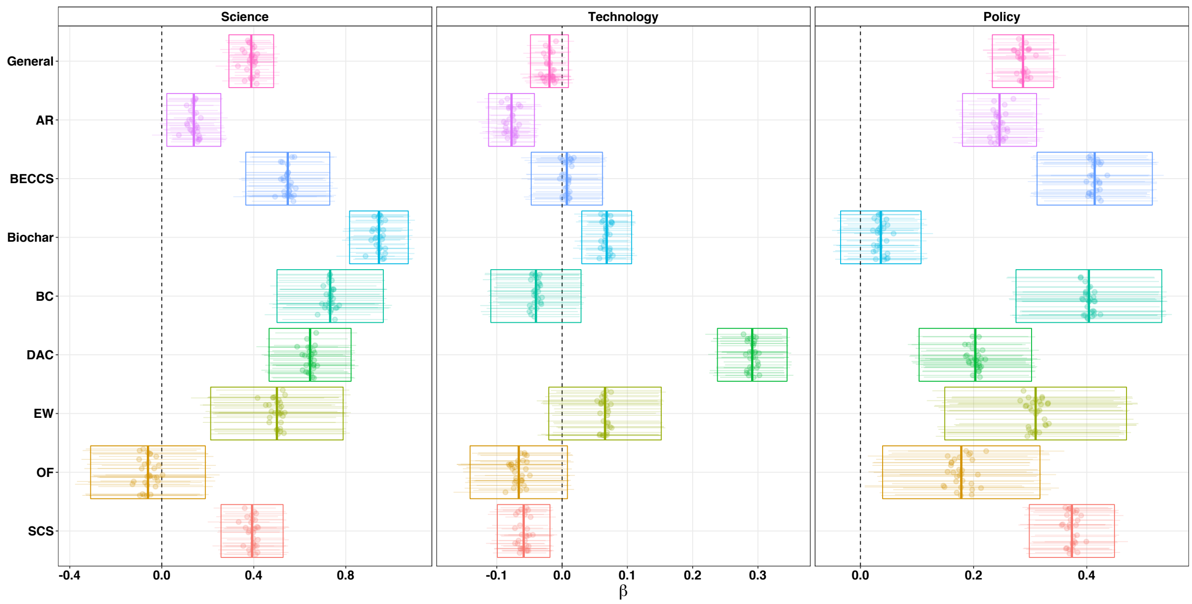

Figure S9: NETs spillovers to science, technology and policy - OLS

Table S5: Coefficients and C.I. Figure S9

	Science		Technology		Policy	
NET	β	$\langle C.I. \rangle$	β	$\langle C.I. \rangle$	β	$\langle C.I. \rangle$
General	0.39	[0.29,0.49]	-0.02	[-0.05,0.01]	0.28	[0.22,0.33]
AR	0.12	[0,0.24]	-0.08	[-0.12,-0.05]	0.24	[0.18,0.31]
BECCS	0.54	[0.35,0.72]	0.01	[-0.05,0.06]	0.42	[0.32,0.52]
Biochar	0.92	[0.79,1.05]	0.06	[0.02,0.1]	0.05	[-0.02,0.12]
BC	0.62	[0.39,0.86]	-0.04	[-0.11,0.03]	0.34	[0.21,0.47]
DAC	0.63	[0.46,0.81]	0.29	[0.24,0.35]	0.21	[0.11,0.3]
EW	0.42	[0.13,0.72]	0.07	[-0.02,0.16]	0.33	[0.17,0.49]
OF	-0.07	[-0.33,0.19]	-0.07	[-0.15,0.01]	0.17	[0.03,0.31]
SCS	0.37	[0.24,0.51]	-0.06	[-0.1,-0.02]	0.34	[0.26,0.42]
Year dummies	✓		✓		✓	
Matched samples	30		30		30	
# of obs.	3392		3392		3392	

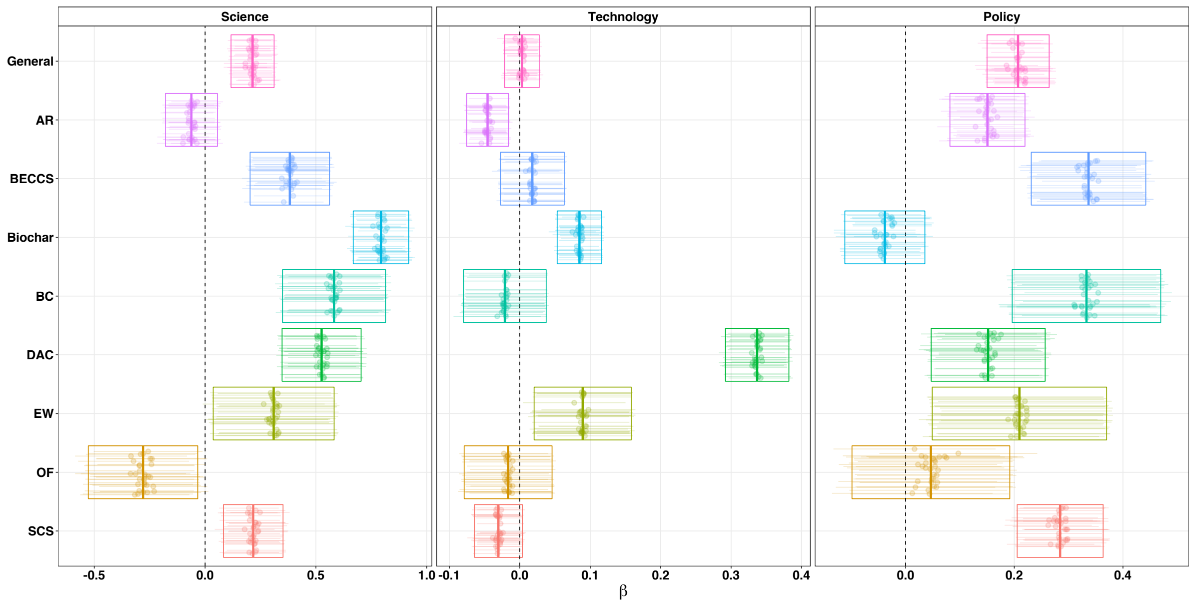

Figure S10: NETs spillovers to science, technology and policy - OLS (climate)

Table S6: **Coefficients and C.I. Figure S10**

	Science		Technology		Policy	
NET	β	$\langle C.I. \rangle$	β	$\langle C.I. \rangle$	β	$\langle C.I. \rangle$
General	0.21	[0.12,0.31]	0.00	[-0.02,0.03]	0.21	[0.15,0.26]
AR	-0.06	[-0.18,0.06]	-0.05	[-0.08,-0.02]	0.15	[0.08,0.22]
BECCS	0.38	[0.2,0.56]	0.02	[-0.03,0.06]	0.34	[0.23,0.44]
Biochar	0.79	[0.67,0.92]	0.08	[0.05,0.12]	-0.04	[-0.11,0.04]
BC	0.58	[0.35,0.81]	-0.02	[-0.08,0.04]	0.33	[0.2,0.47]
DAC	0.53	[0.35,0.7]	0.34	[0.29,0.38]	0.15	[0.05,0.26]
EW	0.31	[0.04,0.58]	0.09	[0.02,0.16]	0.21	[0.05,0.37]
OF	-0.28	[-0.53,-0.03]	-0.02	[-0.08,0.05]	0.05	[-0.1,0.19]
SCS	0.22	[0.08,0.35]	-0.03	[-0.06,0]	0.28	[0.21,0.36]
Year dummies	✓		✓		✓	
Matched samples	30		30		30	
# of obs.	3716		3716		3716	

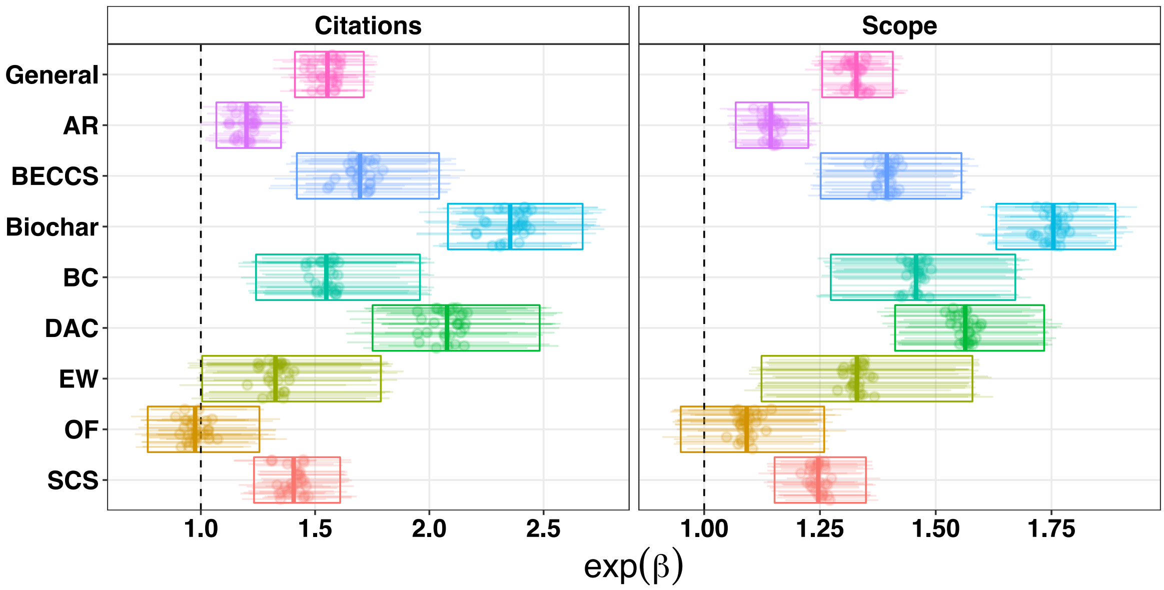

Figure S11: NETs spillovers to science - WoS citations

Table S7: **Coefficients and C.I. Figure S11**

term	Citations exp β	Citations $\langle C.I. \rangle$	Scope exp β	Scope $\langle C.I. \rangle$
General	1.55	[1.4,1.71]	1.32	[1.25,1.4]
AR	1.22	[1.09,1.38]	1.13	[1.06,1.22]
BECCS	1.75	[1.46,2.11]	1.39	[1.25,1.55]
Biochar	2.37	[2.1,2.69]	1.75	[1.63,1.89]
BC	1.36	[1.09,1.73]	1.37	[1.19,1.58]
DAC	2.12	[1.79,2.53]	1.56	[1.41,1.72]
EW	1.26	[0.95,1.71]	1.30	[1.09,1.55]
OF	0.99	[0.78,1.29]	1.08	[0.94,1.25]
SCS	1.40	[1.22,1.61]	1.23	[1.14,1.34]
Year dummies	✓		✓	
Matched samples	30		30	
# of obs.	3392		3392	

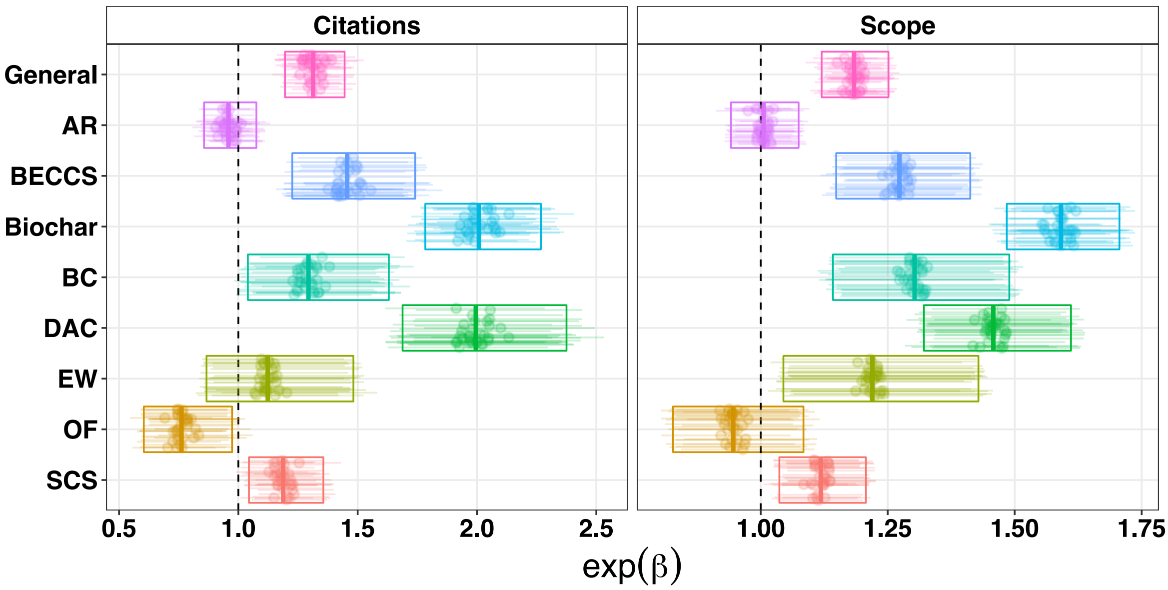

Figure S12: NETs spillovers to science - WoS sample (climate) control

Table S8: Coefficients and C.I. Figure S12

	Citations		Scope	
term	exp β	$\langle C.I. \rangle$	exp β	$\langle C.I. \rangle$
General	1.31	[1.2,1.45]	1.18	[1.12,1.25]
AR	0.96	[0.86,1.08]	1.01	[0.94,1.07]
BECCS	1.46	[1.23,1.74]	1.27	[1.15,1.41]
Biochar	2.01	[1.78,2.27]	1.59	[1.48,1.71]
BC	1.29	[1.04,1.63]	1.30	[1.14,1.49]
DAC	1.99	[1.69,2.38]	1.46	[1.32,1.61]
EW	1.12	[0.87,1.48]	1.22	[1.04,1.43]
OF	0.76	[0.6,0.97]	0.95	[0.83,1.08]
SCS	1.19	[1.04,1.36]	1.12	[1.04,1.21]
Year dummies	✓		✓	
Matched samples	30		30	
# of obs.	3716		3716	

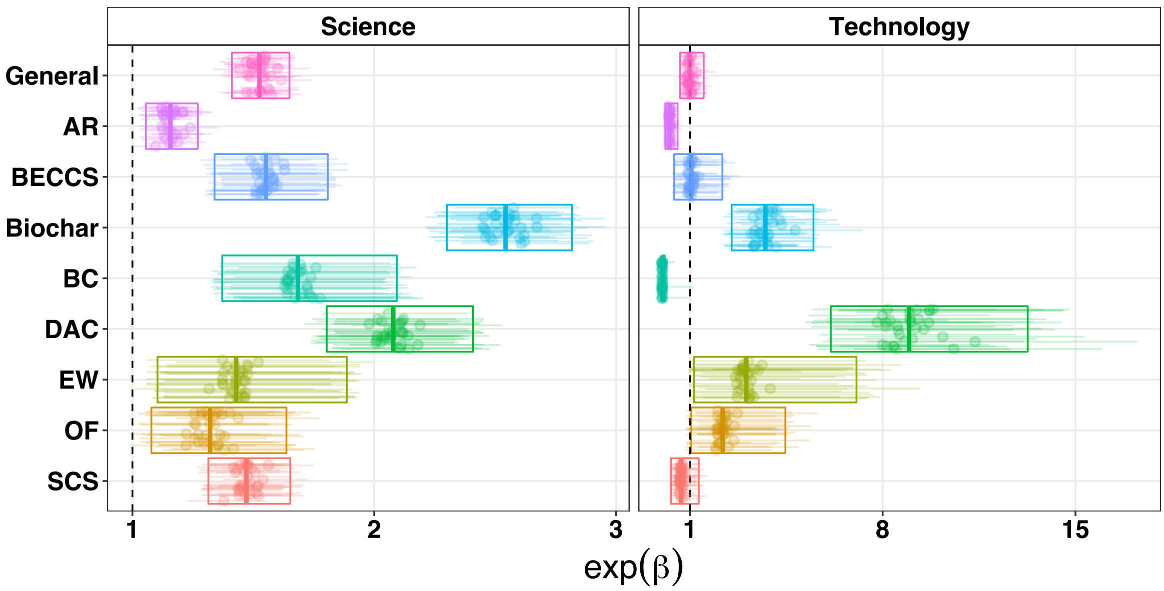

Figure S13: NETs spillovers to science & technology - WoS/RoS sample

Table S9: Coefficients and C.I. Figure S13

	Science		Technology	
term	$\exp\beta$	$\langle C.I.\rangle$	$\exp\beta$	$\langle C.I.\rangle$
General	1.53	[1.41,1.65]	0.99	[0.65,1.5]
AR	1.16	[1.06,1.27]	0.27	[0.11,0.55]
BECCS	1.55	[1.34,1.81]	1.05	[0.43,2.18]
Biochar	2.54	[2.3,2.82]	3.74	[2.52,5.49]
BC	1.68	[1.37,2.09]	✗	
DAC	2.08	[1.8,2.41]	8.96	[6.12,13.27]
EW	1.43	[1.1,1.89]	3.05	[1.14,7.05]
OF	1.32	[1.08,1.64]	2.19	[1.05,4.47]
SCS	1.47	[1.31,1.65]	0.68	[0.31,1.32]
Year dummies	✓		✓	
Matched samples	30		30	
# of obs.	5822		5822	

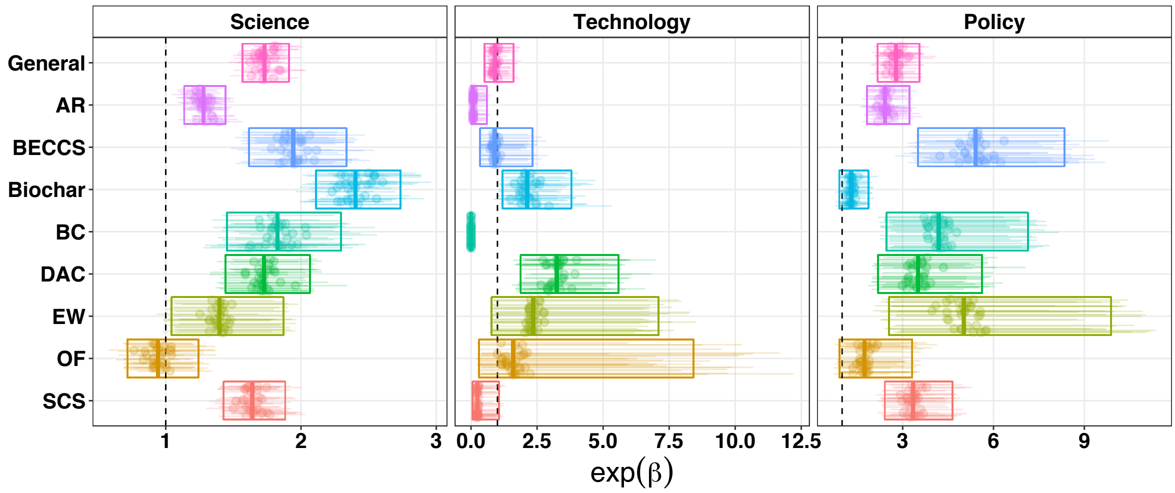

Figure S14: NETs spillovers to science, technology and policy - Additional controls

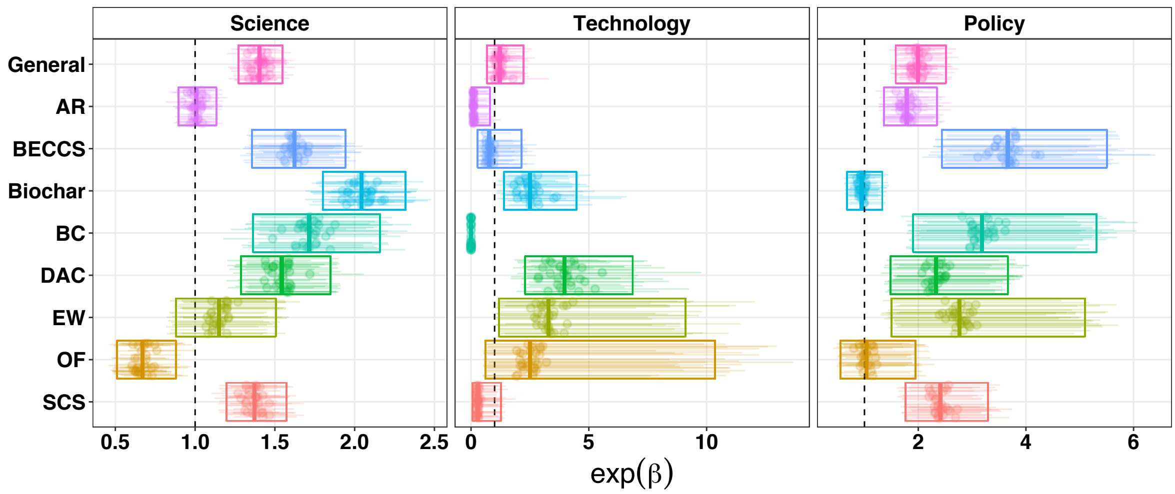

Figure S15: NETs spillovers to science, technology and policy - Additional controls (climate)

Table S10: Coefficients and C.I. Figure S14

	Science		Technology		Policy	
NET	exp β	$\langle C.I. \rangle$	exp β	$\langle C.I. \rangle$	exp β	$\langle C.I. \rangle$
General	1.73	[1.57,1.91]	0.90	[0.51,1.61]	2.78	[2.18,3.55]
AR	1.28	[1.14,1.44]	0.08	[0.01,0.6]	2.42	[1.82,3.22]
BECCS	1.94	[1.62,2.34]	0.90	[0.35,2.32]	5.41	[3.5,8.35]
Biochar	2.40	[2.11,2.74]	2.13	[1.19,3.79]	1.30	[0.91,1.86]
BC	1.83	[1.45,2.3]	✗		4.19	[2.46,7.13]
DAC	1.73	[1.44,2.07]	3.24	[1.88,5.59]	3.51	[2.19,5.63]
EW	1.40	[1.04,1.87]	2.35	[0.78,7.1]	5.02	[2.55,9.89]
OF	0.94	[0.72,1.24]	1.60	[0.3,8.42]	1.74	[0.91,3.32]
SCS	1.64	[1.43,1.88]	0.24	[0.06,1.06]	3.35	[2.41,4.65]
Year dummies	✓		✓		✓	
Controls	✓		✓		✓	
Matched samples	30		30		30	
# of obs.	3378		3378		3378	

Table S11: Coefficients and C.I. Figure S15

	Science		Technology		Policy	
NET	exp β	$\langle C.I. \rangle$	exp β	$\langle C.I. \rangle$	exp β	$\langle C.I. \rangle$
General	1.40	[1.27,1.55]	1.22	[0.67,2.23]	1.99	[1.58,2.51]
AR	1.01	[0.89,1.13]	0.10	[0.01,0.81]	1.79	[1.36,2.34]
BECCS	1.62	[1.36,1.94]	0.78	[0.28,2.14]	3.66	[2.44,5.5]
Biochar	2.04	[1.8,2.32]	2.50	[1.4,4.47]	0.95	[0.68,1.33]
BC	1.72	[1.36,2.16]	✗		3.18	[1.91,5.31]
DAC	1.54	[1.29,1.85]	3.97	[2.3,6.86]	2.33	[1.48,3.66]
EW	1.15	[0.88,1.51]	3.29	[1.19,9.11]	2.77	[1.5,5.1]
OF	0.67	[0.51,0.88]	2.50	[0.6,10.36]	1.04	[0.55,1.95]
SCS	1.37	[1.2,1.57]	0.29	[0.07,1.28]	2.41	[1.76,3.3]
Year dummies	✓		✓		✓	
Controls	✓		✓		✓	
Matched samples	30		30		30	
# of obs.	3518		3518		3518	

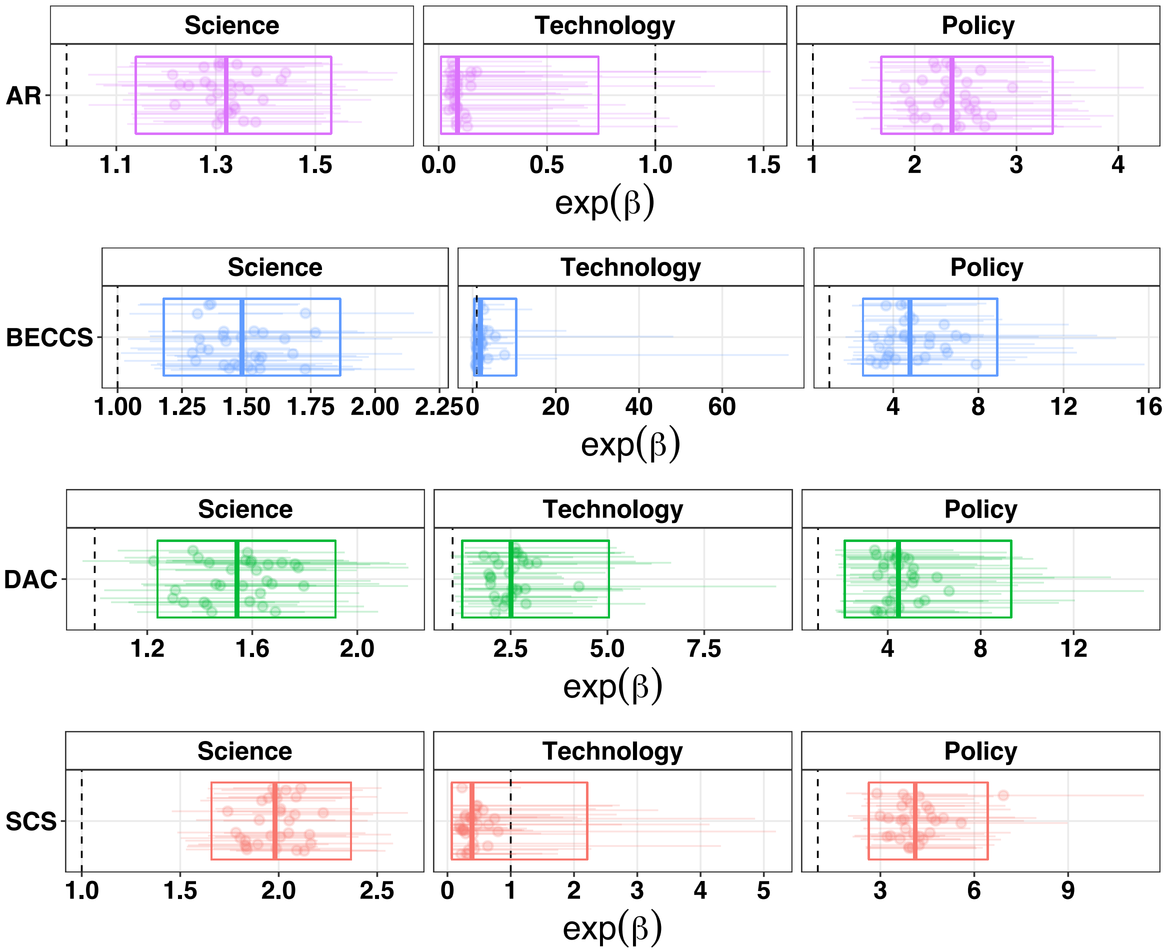

Figure S16: NETs spillovers to science, technology and policy - Separate matching control (AR) Afforestation and Reforestation. **(BECCS)** Bio-energy with Carbon Capture ans Storage. **(DAC)** Direct Air Capture. **(SCS)** Soil Carbon Sequestration.

S7 Geography

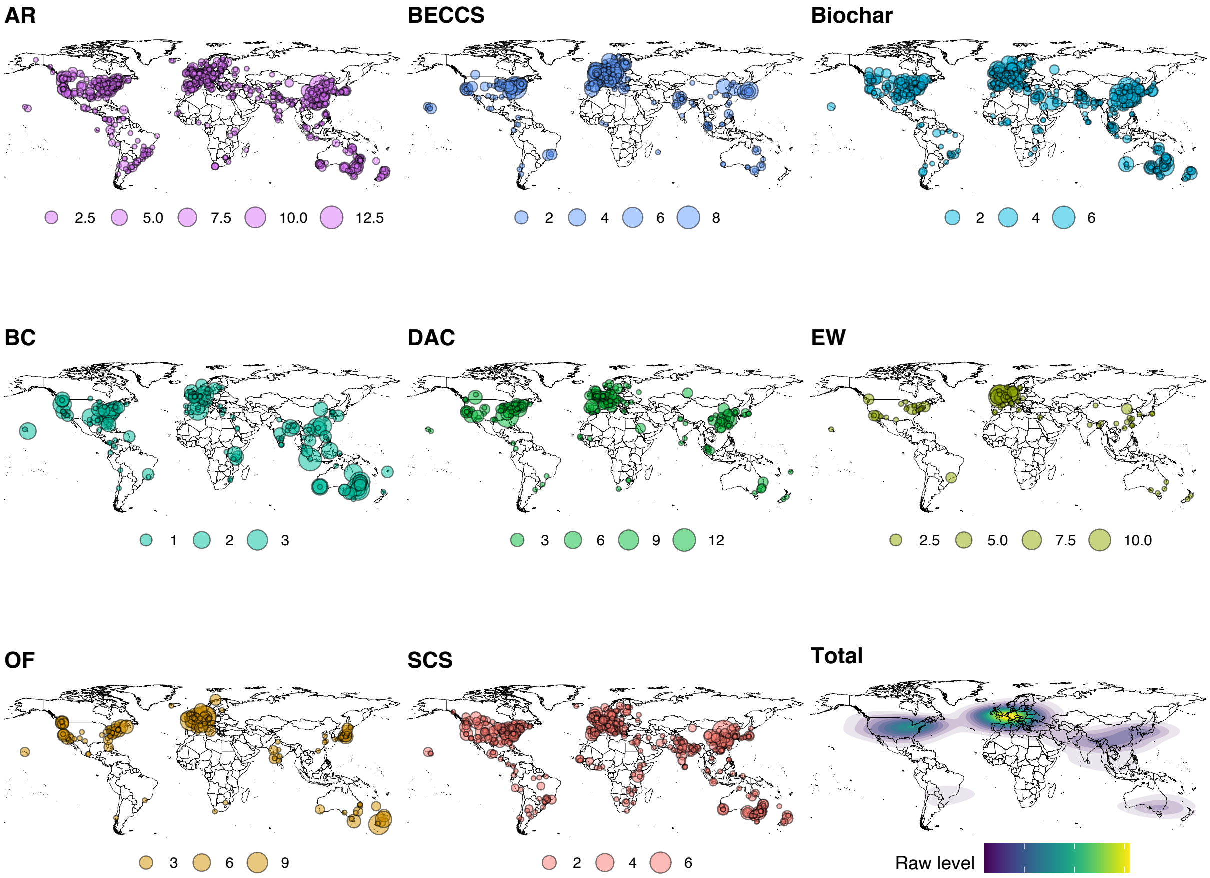

Figure S17: Geographical distribution of NETs research. Geographical distribution of negative emissions articles at city-level by category (% values). The total map depicts the aggregate unweighted density of cities where NETs research is performed. Geo-localized data are described in section 4.3.

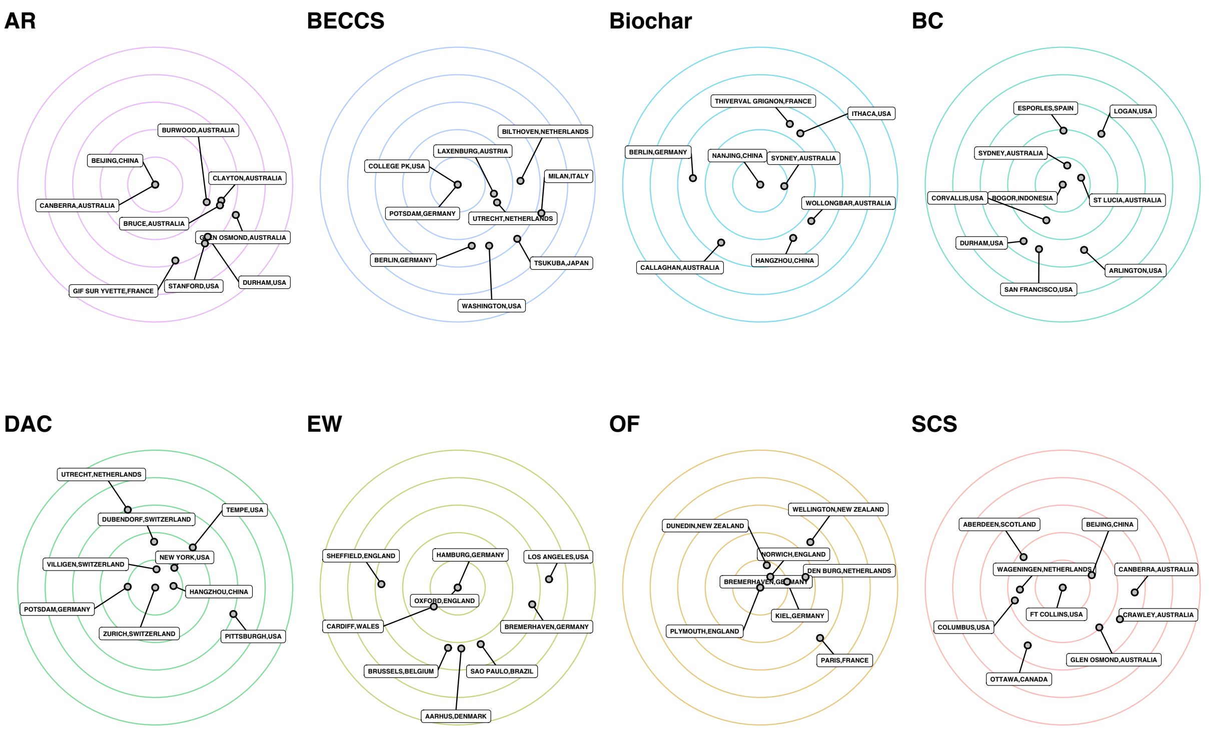

Figure S18: Most central cities. The most central cities for each NET-specific collaboration network. Centrality is measured by computing nodes' strength in the collaboration network based on affiliation data (see section 4.3).

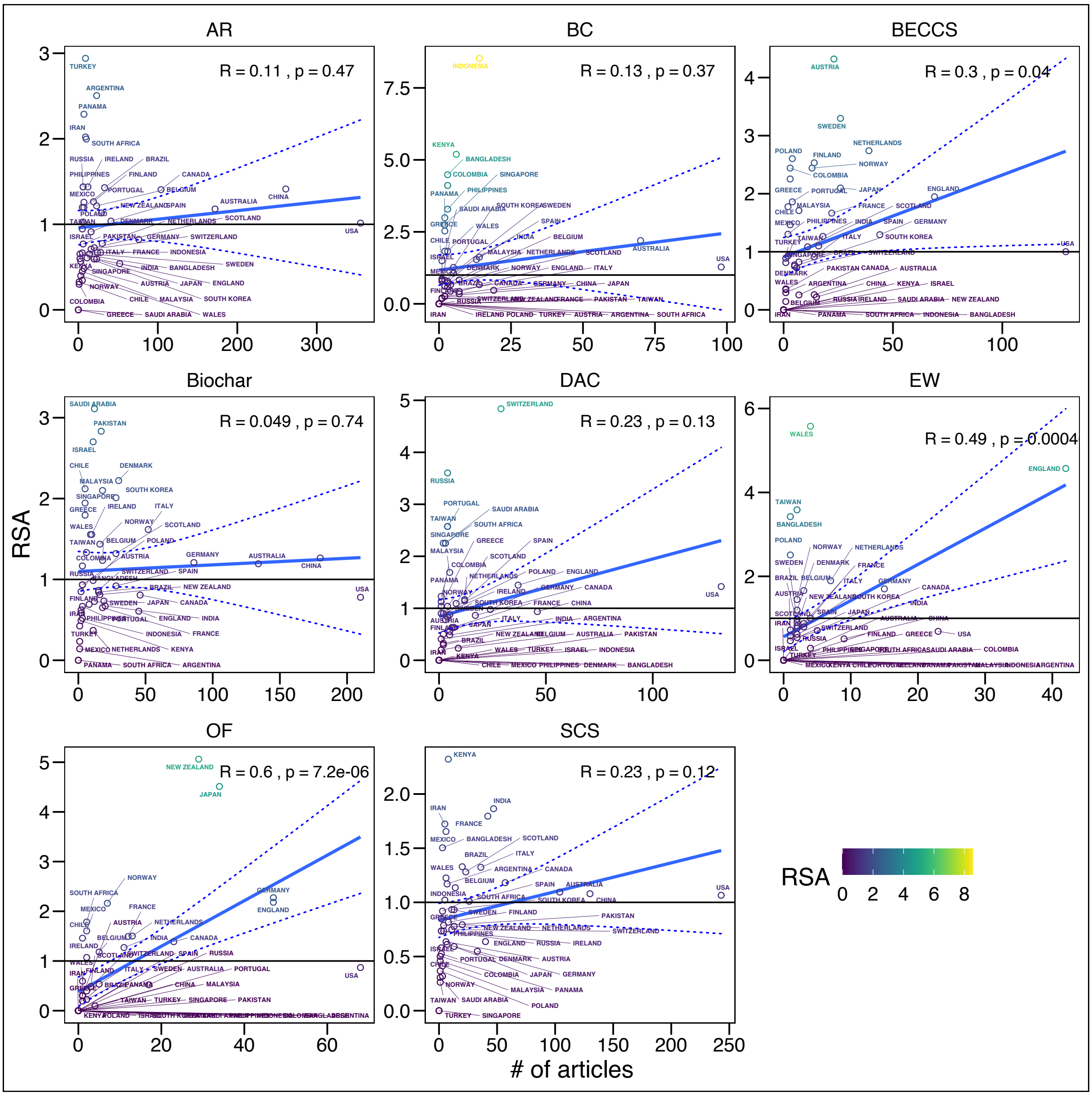

Figure S19: Correlation between RSA and total number of articles. Scatter plots for a subset of countries (i.e., countries with at least 10 articles in NETs) for each NET category. The RSA horizontal reference line fixed at 1 indicates relative advantage.