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LETTER

The public use of early-stage scientific advances in carbon dioxide removal: a science-technology-policy-media perspective

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Abstract

While Carbon Dioxide Removal (CDR) solutions are considered essential to meet Paris Agreement objectives and curb climate change, their maturity and current ability to operate at scale are highly debated. The rapid development, deployment, and diffusion of such methods will likely require the coordination of science, technology, policy, and societal support. This article proposes a bibliometric approach to quantify the public use of early-stage research in CDR. Specifically, we employ generalized linear models to estimate the likelihood that scientific advances in eight different carbon removal solutions may induce (i) further production of scientific knowledge, (ii) technological innovation, and (iii) policy and media discussion. Our main result is that research in CDR is of significant social value. CDR research generates significant, positive, yet heterogeneous spillovers within science and from science to technology, policy, and media. In particular, advances in *Direct Air Capture* spur further research and tend to result in patentable technologies, while *Blue Carbon* and *Bio-energy with Carbon Capture and Storage* appear to gain relative momentum in the policy and public debate. Moreover, scientific production and collaborations cluster geographically by type of CDR, potentially affecting long-term carbon removal strategies. Overall, our results suggest the existence of coordination gaps between science, technology, policy, and public support.

1. Introduction

Increasing evidence suggests that meeting ambitious climate targets will require removing large stocks of carbon dioxide from the atmosphere [1–3]. Tackling climate change by removing CO_2 from the atmosphere has been a tantalizing idea since the 1980s [4]. Planting trees, or rather designing forest management programs, has been among the first solutions proposed in the literature [5]. Over time, a broader and more sophisticated set of solutions have been developed, generally referred to as *Negative Emissions Technologies* (NETs) or CDR methods, which include (i) solutions enhancing existing natural processes that remove carbon from the atmosphere and the oceans, and (ii) those using chemical processes to, for example, capture CO_2 directly from the ambient air and store it elsewhere [2].

The literature on mitigation pathways now mentions carbon removal as a pivotal element in meeting the Paris Agreement objectives and tackling global warming [2, 6, 7]. In most scenarios, the transition toward net zero emissions will require the extensive deployment of CDR solutions to balance the inevitable difficulties of cutting short-term emissions even more drastically [8]. However, as of today, there are doubts on the possibility of immediate, large-scale deployment of CDR solutions, and their use as a technical or policy panacea may be implausible and even hazardous [9–12]. 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 [13–18]. Indeed, the evidence about how different CDR solutions could fully develop and diffuse is still inconclusive. However, the history of technological change clearly shows that rapid diffusion of disruptive technologies may vastly benefit from coherent science-technology-policy landscapes [19, 20].

This article examines the effectiveness of CDR research in producing knowledge spillovers, and its relationship with innovation, policy, and media. In particular, we quantify the likelihood that early-stage scientific advances across eight carbon removal solutions may (i) stimulate the production of further scientific advances, (ii) foster technological innovation, and (iii) enter the policy and public debate. Moreover, we investigate the geographical distribution of CDR research, using relative comparative advantage to identify the scientific specializations of countries and single out the main research hubs of the global innovation system.

Different CDR solutions have been mostly evaluated along five dimensions: negative emissions potential (i.e. Gt Ceq per year), energy requirements, land and water usage, and economic costs (US$ per t Ceq) [21, 22]. Overall, no universally superior option has been identified [23]. This article adds novel dimensions to the multi-faceted comparison of various carbon removal technologies and, to the best of our knowledge, provides the first quantitative estimates of the spillovers of CDR research. To do so, we integrate citation data from scientific articles with information from patents, policy documents, and non-technical media mentions (e.g. social media, newspapers, blogs), from multiple data sources; namely: Web of Science (WoS), Microsoft Academic Graph (MAG), Reliance on Science (RoS), and Altmetric (see sections 2.1 and Data SI for more details).

We focus on the following list of eight solutions: Afforestation and Reforestation (AR), Bioenergy with Carbon Capture and Storage (BECCS)[11], Biochar, Blue carbon (BC), Direct Air Capture (DAC)[12], Enhanced weathering (EW), Ocean fertilization (OF), and Soil Carbon Sequestration (SCS). We occasionally group methods following the approach used in the 'The State of CDR' 2024 report [3]. In particular, we distinguish between *conventional* and *novel* solutions. The former class refers to methods that are well established and widely reported by countries as part of land use, land-use change and forestry activities (AF, BC and SCS), while the latter includes solutions that are promising yet at an earlier stage of development (in our context: BECCS, Biochar, DAC, EW, and OF).

Leveraging methods developed in the innovation and applied economics literature, we measure the use of scientific research, i.e. its spillovers, through the analysis of citation networks, reconstructed on the basis of 20 years of data on scientific production [27–29]. However, we move beyond citations in the scientific domain to incorporate knowledge flows to technological innovations (i.e. patents) and to the policy and public discourse (i.e. policy documents and media outlets) [30–32]. Firstly, we document the broader public impact of CDR research through mentions in different media channels, integrating large data sources that link the scientific literature to several different public domains. Next, we model spillovers through regression techniques [33, 34]; finally, we use geo-localization and network analysis techniques to study specialization and identify countries where scientific advances contribute the most to policy or technological development.

This article points towards coordination gaps between science, technology, and policy in the domain of carbon removal solutions. Our results, based on the first wave of CDR scientific developments, suggest that (i) public use of scientific knowledge in carbon removal is substantial, (ii) however, CDR solutions are very heterogeneous, with few removal methods solidly linked to inventions; further, (iii) world-wide research related to CDR is geographically concentrated around hubs with different specializations. Interestingly, DAC appears as the most promising solution, with significant knowledge spillovers across all dimensions. However, policy and media are relatively more focused on other methods (BECCS).

2. Data and methods

2.1. Data and controls

Our analyses employ four main sources of data: Web of Science (WoS), Reliance on Science (RoS), Microsoft Academic Graph (MAG—via SciSciNet), and Altmetric. WoS is a large global citation database maintained by the private company Clarivate,

[11] BECCS articles do not include standard CCS methods to isolate the negative emissions technology papers from the literature related to point capture. To do this, our procedure is to set exclusions for co-firing, co-generation and coal in the query used to retrieve BECCS articles, as in [24, 25].

[12] DAC does not explicitly include storage options [26]; see section 2.1 and Data SI for more details.

collecting information on millions of research articles. RoS is a publicly available database collecting citations of scientific articles by patents. [35]. SciSciNet is a large open data lake supporting 'Science of Science' research, which is based on MAG [36]. Altmetric is a curated database collecting metrics complementary to standard citation-based data, such as mentions on a diverse set of outlets.

To identify CDR articles, we look at keywords, titles, and abstracts in WoS—as previously done in the literature [24–26]. We retrieve 3301 articles published between 1998 and 2017, and parse them into eight different CDR solutions (see section Data SI). The queries we used to identify DAC articles do *not* explicitly include 'storage', contrary to BECCS and in line with previous studies [24, 25]. All articles returned by the keywords search with no explicit reference to a specific CDR solution in their titles or abstracts are placed in a 9th CDR category labeled *General* (see section Data SI for additional details on the articles and a complete list of the full-length queries). We also exclude from our analyses articles related to IAM-based mitigation scenarios, which tend to gather disproportionate attention to certain removal methods (e.g. BECCS; see section Data SI). Further, we geo-localize CDR articles to uncover regions' specialization in CDR methods. Exploiting authors' affiliations, we use OpenStreetMap and the R package *tmap* to identify the coordinates of the cities (and countries) linked to each article. We successfully geo-localize 3255 articles out of 3301 ($\sim 98\%$ of the overall set). Articles with authors affiliated with institutions based in different countries are counted separately in each country.

Next, we tally the mentions (citations) of each CDR article using WoS and Altmetric for mentions by other research articles; RoS and Altmetric for mentions by patents; and Altmetric for mentions by policy documents, mainstream media outlets, blogs, and social media platforms such as Facebook or Twitter/X[13].

We also complement Altmetric with SciSciNet to retrieve several variables that we employ as control covariates potentially affecting spillovers, e.g. team size, number of references. Our sample include CDR articles collected up to 2017 and spillovers (i.e., citations and mentions) up to the end of 2021. This time window is necessary to compare articles in terms of impact. Scientific articles accrue citations over time, and thus, scientometric comparisons often include a time constraint and a normalization [37–40]. In our setting, a sufficiently long time window is even more necessary since we do not only look at citations coming from other scientific articles but also mentions collected from sources that pick up scientific results at a lower pace (i.e. patents and policy documents [41–43]). Different samples/alternative specifications do not affect any of the main results (section Regressions SI).

A simple comparison of mentions among different CDR methods, although possibly interesting, might result in biased estimates and misleading conclusions. A quantitative comparison, as the one proposed in this work, requires the identification of a suitable control group to compare with, in a way to wash away mentions that can be expected ex-ante for a generic scientific advance. In particular, to have a clear benchmark when comparing articles' impact, an ideal setting would comprise articles related to CDR and articles perfectly equal in all possible dimensions except for their main focus (i.e. CDR vs. non CDR). Therefore, following the literature on spillover quantification [27, 28], our analysis builds on a systematic comparison of CDR papers with comparable non-CDR ones. We create controls of two types; *baseline*, comprising articles from any non-CDR research area, and *climate*, comprising articles from non-CDR but climate-related research. In the baseline case, we start by forming, for each CDR article, a list of up to 10 non-CDR articles selected at random from those published in the same year and the same journal. This produces a pool of about $23K$ articles. From such a pool, we create a one-to-one matched control group, drawing one article (at random) from the list of each CDR article. For our regression analyses, we actually create 30 such matched control groups, repeating the drawing process (without replacement). These are added, one at a time, to the CDR articles, resulting in 30 control-augmented data sets on which we fit our regression models 30 separate times. Performing such multiple fits is a way to gauge stability of regression results; each control group is built to match CDR articles in terms of age (publication year), and quality (publication venue), but alternating control groups lets us verify that our conclusions are not driven by chance in creating the matches. These controls are referred to as *baseline controls*. Further, we use exactly the same procedure to create 30 one-to-one matched *climate control* groups. Here, the list of up to 10 non-CDR articles associated with each CDR article is selected from climate-related publications retrieved by querying WoS as in [44, 45], which produces a pool of about $20K$ articles (sections Data SI and Regressions SI).

To be used in our analysis, non-CDR articles must have information from all the data sources we employ (i.e. WoS, RoS, SciSciNet, and Altmetric). In practice, we cannot construct lists of non-CDR articles (baseline controls) or non-CDR climate-related articles (climate controls) for all 3301 CDR articles. The number of CDR articles for which we can produce matched controls with full information is 1467 in the case of baseline controls, and 1502 in the case of climate controls. Considering only these CDR articles

[13] Notice that Altmetric tracks mentions to media and public policy sources globally, with no language restrictions. See section Data SI for details.

together with their baseline control groups produces 30 'samples' of size 3136 (baseline controls) and 30 'samples' of size 3212 (climate controls) to run our regressions. Sacrificing about half of the retrieved CDR articles to create usable controls is a stark toll, as it may introduce different biases in place of the ones we are trying to eliminate. Reassuringly though, fitting regressions with larger/different sets of CDR articles provides the same insights (section Regressions SI).

2.2. GLM regressions

Tallies for CDR solutions are normalized against control tallies. In more detail, we compute the average number of citations (or mentions), and we take the ratio with respect to the control group to easily gauge the relative attention that CDR articles are collecting in several dimensions.

Beyond the simple count of mentions of CDR articles (e.g. in other papers, in patents, in policy documents), we employ Generalized Linear Models (GLMs) to estimate the multidimensional spillovers of CDR-related research. Specifically, we use negative binomial regression to model mention counts in other scientific articles (i.e. forward citations), and logistic regressions to model mention occurrences (binary; yes/no) in patents, policy documents, and media outlets. Our main model specification can be written as

$$g\left(E\left(S_{ikt}|\mathrm{CDR}_{ik},T_{it},\mathbf{X}_i\right)\right)=\alpha+\sum_k\beta_k\mathrm{CDR}_{ik}+\sum_t\gamma_t T_{it}+\boldsymbol{\delta}^{\mathbf{T}}\mathbf{X_i}\quad(1)$$

where i indexes articles; k indexes the eight CDR solutions plus the *General* CDR category; and t indexes years. S_{ikt} are responses (counts of forward citations, or binary values indicating the occurrence of a mention in patents, policy documents, or media outlets); CDR_{ik} are CDR dummies (they are all equal 0 if article i belongs to the control group); T_{it} are year dummies; and $\mathbf{X}_i$ is a vector of control covariates (see section Regressions SI for more details). In a GLM, the link function connects the additive expression on the right of the equal sign, which is linear in the parameters (i.e. the β_k's, the γ_t's and the entries of δ), with the conditional expected value of the response variable. If we let $\mu=E(S_{ikt}|\mathrm{CDR}_{ik},T_{it},\mathbf{X}_i)$, the link function of a negative binomial regression is $g(\mu)=\log\mu$, and that of a logistic regression is $g(\mu)=\log\frac{\mu}{1-\mu}$.

The four spillover regressions (on science, technology, policy, and media) are all fitted on 30 data sets—each comprising the same CDR articles and alternative baseline control groups. In each fit $m=1,\ldots,30$, we consider the exponentiated coefficient estimates $\exp\{\hat{\beta}_{km}\}$, and the corresponding 95% confidence intervals $[L_{km},U_{km}]$. In a parallel exercise, the four spillover regressions are fitted on another 30 data sets—each comprising the CDR articles and alternative climate control groups. Additional robustness checks are shown in the SI (section Regressions SI).

In the negative binomial regression, each exponentiated coefficients can be interpreted as the Incident Rate Ratio (IRR) of the corresponding CDR solution with respect to the control group (all CDR dummies equal to 0). Thus, large estimates and confidence intervals entirely above 1 provide evidence of significant impact. The same holds for the logistic regressions, where exponentiated coefficients can be interpreted as Odds Ratios (OR) [46].

2.3. Geographical specialization

To capture the relative specialization of countries in specific CDR methods, we employ a metric called Revealed Scientific Advantage (RSA). Such a measure is based on the well-known Revealed Comparative Advantage (RCA), initially developed to analyze comparative international trade advantages among countries [47]. Later, the same metric was extensively used in several applications beyond trade [48, 49]. In our setting, for each country l and CDR solution k, we define it as

$$\mathrm{RSA}_{lk}=\frac{\frac{w_{l,k}}{\sum_k w_{l,k}}}{\frac{\sum_l w_{l,k}}{\sum_{l,k} w_{l,k}}}\qquad(2)$$

where $w_{l,k}$ is the number of articles belonging to CDR solution k whose author affiliations are located in country l. Note the tallies of publications here are aggregated over time and over cities belonging to each country. RSA values greater the 1 signal relative specialization. Technology and policy coverage are defined as: $\mathrm{TC}_k=\frac{wt_{l,k}}{w_{l,k}}$ and $\mathrm{PC}_k=\frac{wp_{l,k}}{w_{l,k}}$ where $wt_{l,k}$ and $wp_{l,k}$ are, respectively, the number of articles cited by a patent or a policy document, belonging to CDR solution k whose author affiliations are located in country l. Additional details are contained in the SI (see also sections 2.1, Data SI and Geography SI).

3. Results

3.1. The rise of CDR research within and beyond science

Our exploration of the landscape of CDR research starts by mapping the general trends that characterize the rise of negative emissions as a scientific sub-field, and how this line of research has been gaining traction in the last 20 years.

Figure 1 shows the number of articles per year, partitioned by CDR solution, their geographical distribution and the share of papers relating to conventional vs. novel methods. This simple comparison already highlights differences in the scientific specializations of countries. Negative emissions research is growing fast, scientific production is largely dominated by the US and China, but differences apply when looking at conventional vs novel solutions. Indeed,

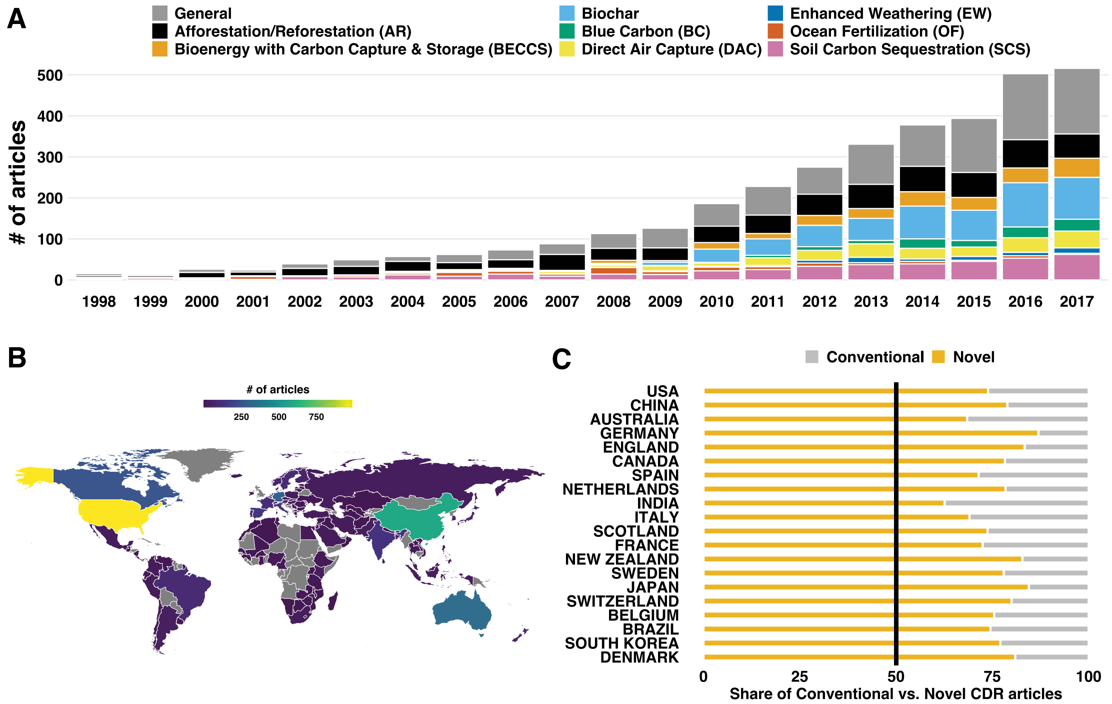

Figure 1. CDR research in the last 20 years. (A) CDR articles from 1998 to 2017 collected through a WoS text search. In addition to the eight color-coded CDR solutions, the category *General* is defined residually (it includes articles that match CDR keywords but do not have solution-specific text patterns in their titles or abstracts). (B) Geographical distribution of CDR articles (raw counts). (C) Share of novel vs. conventional CDR articles for the top 20 countries (by total number of CDR articles).

the first wave of scientific advances in CDR has been already disproportionately focused on the development of novel methods.

CDR methods are not all alike: crucial differences have been reported in relation to measurement, verification, accounting and durability of stored CO_2 [50], as well as to costs and requirements [21, 22]. Against this background, we find stark heterogeneity in their knowledge bases and scientific spillovers (see also section Knowledge flows SI).

In particular, we map the knowledge bases (i.e. the scientific fields upon which CDR methods rely) and scientific spillovers (i.e. scientific fields influenced by advances in CDR). Conventional and novel solutions differ in both aspects, and scientific overlaps are limited. As expected, conventional solutions are scientifically grounded in soil science and ecology, while solutions such as BECCS and DAC are engineering-driven. Perhaps more interestingly, as CDR solutions build on different scientific fields, the directions of potential spillovers follow accordingly. To better illustrate this, we show the bipartite networks linking each CDR solution with the fields most frequently cited (see section Knowledge flows SI for more detail) in its knowledge base (figure S8(A)) and in the set of its scientific spillovers (figure S8(B)). Overall, the heterogeneity in the former is closely reflected in the latter. Some CDR solutions can certainly be compatible if used together, but they do not appear to be synergic in the knowledge they build upon and produce. As technical development and diffusion require time-expensive knowledge accumulation [16, 17], this result points to the urgency of an early definition of clear and technologically targeted carbon removal strategies.

3.2. Multidimensional impacts of different CDR solutions

Our key result is that CDR research consistently produces larger impacts than its control groups across science, technology, policy, and media. This is already visible from relative mention counts (see figure 2). As expected, the relative impact is lower when CDR articles are matched against the climate control group (climate change is a very impactful area of research per se). Interestingly enough, however, when compared to articles within the climate change literature, CDR research shows a disproportionately larger link to actual technological developments (results are also confirmed through regression analyses; see section Regressions SI).

Figure 3 breaks down results across CDR solutions. Impacts are shown as bar-plots for what concerns novel and conventional CDR solutions (figure 3(A)) and as radar charts (figure 3(B)) of the mentions normalized against baseline controls (see also figure S12 for robustness). While scientific spillovers are similar across CDR solutions, marked differences emerge in other impact dimensions. For instance, BECCS and BC are relatively more popular than other solutions in policy documents and media outlets, and EW is intensively discussed in the

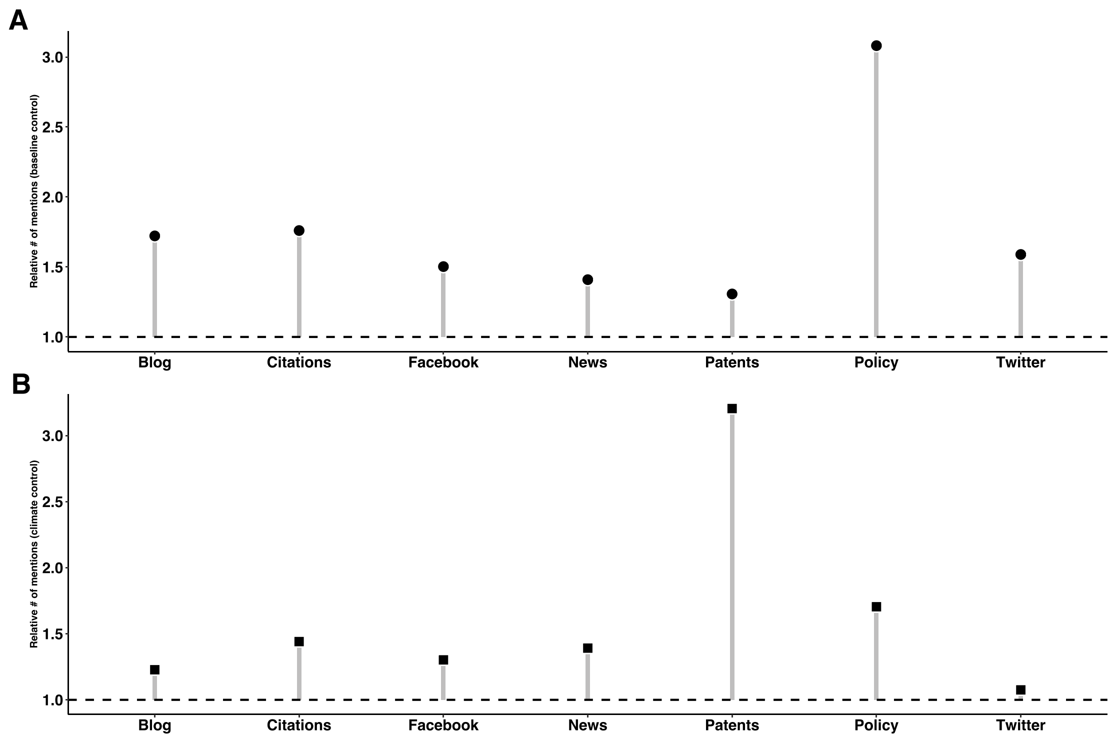

Figure 2. Public use of CDR scientific advances. Bar-plots illustrating the relative number of mentions that CDR articles collect with respect to the one-to-one matched control groups (i.e. ratio of counts). Values above 1 signal a larger number of citations/mentions than expected from the control group. (A) Multi-dimensional impact of CDR research compared to the baseline control. (B) Multi-dimensional impact of CDR research compared to the climate control. Additional results using regression techniques are provided in figure S18.

news and—disproportionately—on social media. At the same time, most CDR solutions do not display strong technological spillovers, with the exception of DAC—whose articles are mentioned by patents seven times more frequently than controls. AR is, on average, across dimensions, the least impactful CDR solution. Conversely, BC appears to exert the largest average impact, though its articles are mentioned by patents less frequently than controls, suggesting a concerning lack of technological impulse. Interestingly, these patterns are largely confirmed even when CDR articles are compared against the climate controls. In particular, the link between DAC articles and patent mentions appears to be even stronger (see figure S12).

3.3. Quantifying spillovers in science, technology, policy, and the media

In this section, we continue our investigation of the impact of CDR research on science, technology, policy, and the media, modeling the multidimensional spillovers taking into account potential confounding variables as well as addressing the possible variability related to the matching procedure.

Since, for any given article, mentions in other scientific articles (i.e. forward citations) are more abundant than mentions in patents, policy documents or media outlets, we employ different Generalized Linear Models. In particular, we employ a negative binomial regression to model mention counts in scientific articles, and three logistic regressions to model mention occurrences in patents, policy documents, and media outlets (these are viewed as binary; an article is either mentioned or not). We fit these regressions resorting again to controls to balance our comparisons, and repeating the fits several times (see section 2.1).

Figure 4 and table 1 summarize the results for the four spillover regressions (on science, technology, policy, and media). In particular, we present exponentiated coefficient estimates and corresponding 95% confidence intervals. Exponentiated coefficients are interpreted as Incident Rate Ratios (IRR; negative binomial regression) or Odds Ratios (OR; logistic regression) of CDR solutions vs controls, and we evaluate these effect sizes capturing both standard statistical accuracy (confidence intervals) and stability to control selection.

Overall, our regression analysis confirms that CDR research generates larger spillovers than controls (except for technological spillovers linked to conventional methods, figure 4(A)). More in detail, despite both novel and conventional CDR methods look scientifically promising, some differences emerge in the other dimensions. Novel CDR methods show positive technological spillovers, but relative fewer mentions

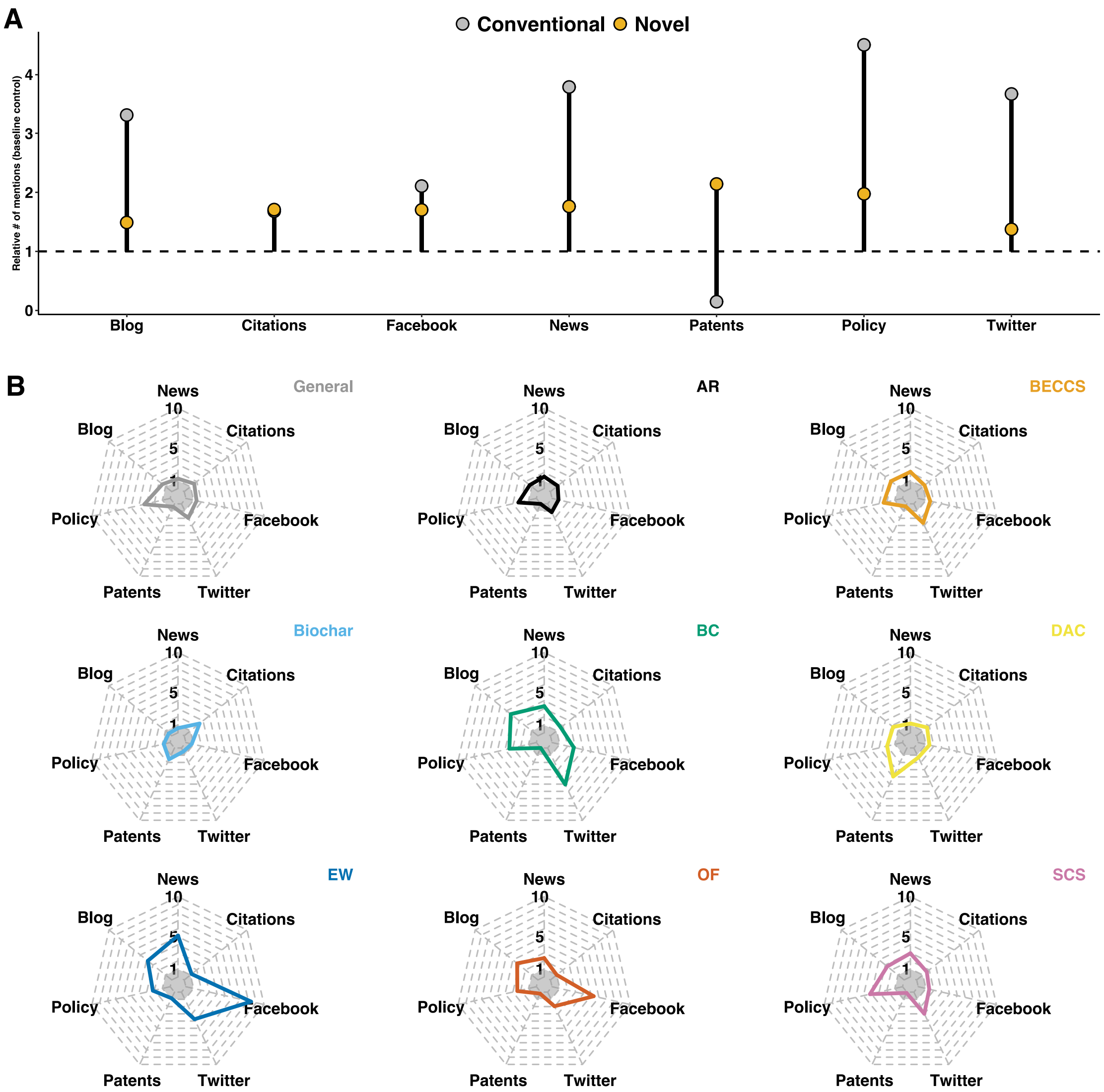

Figure 3. Multidimensional impacts of CDR research. (A) Bar-plots illustrating the relative number of mentions that novel and conventional CDR articles collect with respect to the one-to-one matched control groups (i.e. ratio of counts). Values above 1 signal a larger number of citations/mentions than expected from the control group. (B) For each CDR solution, a radar chart shows mentions of articles belonging to the solution in other scientific articles (citations), patents, policy documents, and various traditional and social media outlets (news, blogs, Facebook, Twitter/X). Mentions are normalized (i.e. ratio of counts) to baseline controls (articles matching publication year and venue but unrelated to CDR). Values greater than 1 signal a positive effect with respect to the control group. The grey area at the center of radar charts signals a ratio ≤ 1. The top-left chart concerns the residual category ***General*** (CDR articles that could not be attributed to specific CDR solutions). Next, left to right and top to bottom: **(AR)** Afforestation and reforestation; **(BECCS)** Bio-energy with Carbon Capture and Storage; **(Biochar)** Biochar; **(BC)** Blue Carbon; **(DAC)** Direct Air Capture; **(EW)** Enhanced Weathering; **(OF)** Ocean Fertilization; **(SCS)** Soil Carbon Sequestration.

from policy and media outlets than conventional ones. Such results might be partially explained by the technological content (see also section Knowledge flows SI) of some CDR options and the familiarity that characterizes conventional CDR methods, such as AR [51]. It is also worth mentioning that the direction of casualty in this case (i.e. familiarity-policy/media interest) is not straightforward and cannot be assumed from our empirical exercise. When looking at specific CDR, however, the picture that emerges is nuanced. Biochar, BC and DAC stand out as the solutions with the most significant impacts on science—on average across multiple fits, their articles collect 2.12 (Biochar), 2.06 (BC), and 1.49 (DAC) times more citations in scientific journals than baseline controls (figure 4(B-Science), table 1 left-most panel). However, only DAC and Biochar show significant impacts also on technological development, with a marked gap in favor of DAC—on average across fits, their articles are 3.45 (DAC) and 2.10 (Biochar) times more likely to be mentioned in patents than baseline controls (figure 4(B-Technology), table 1 center-left panel). Considering policy documents and media outlets, BC and BECCS stand out as the solutions with the most significant likelihood of being mentioned (figures 4(B-Policy) and (B-Media), table 1 center-right and right-most panels). More in detail, DAC is the only carbon removal solution