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# Climate partners of Helsinki: Participation-based structures and performance in a city-to-business network addressing climate change in 2011–2018

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ABSTRACT

Private actors are important for urban climate action, because the public sector can control the carbon footprint of a city only partly. Public-private partnerships have been created through different voluntary approaches, such as city-level voluntary networks for companies with the aim to engage private actors in climate change mitigation and to support learning processes by bringing different actors together. If these processes are to happen, network members should connect with each other through voluntary networking activities. These connections can be studied using methods from network science. As a case example, we study the event-participation-based structures of the Climate Partners network of the City of Helsinki between 2011 and 2018, and develop an index to measure whether active event participation by a company is associated with taking more ambitious mitigation measures. The results show that the network manages to bring together companies from different fields but has difficulties with engaging them and encouraging ambitious climate goals. Our results can help to further develop networking activities. The tools we develop and share allow the replication of the analysis for other data sets, offering a basis for a comparative analysis of different networks. This opens new horizons for studying public-private networking and its effects.

## 1. Introduction

Cities and other subnational actors, such as private businesses, are important actors in climate change mitigation (Bulkeley, 2010; Revi et al., 2014; van der Heijden, 2018; van der Heijden et al., 2018; Kuramochi et al., 2020). Kuramochi et al. (2020) suggest that subnational actors could become the driving force behind meeting the Paris Agreement goals. The shift from government to governance has increased the perceived importance of the private sector and participatory approaches in steering urban affairs, such as urban climate governance (Gupta et al., 2015), often based on network weaving and facilitation-focused public and private leadership instead of command and control (Bodin, 2017).

The actions of private actors create a significant share of greenhouse gas emissions, and reducing them is a central target of climate

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governance (Abbot, 2018) and an economic incentive for businesses (Gouldson et al., 2015). Therefore, public authorities need to cooperate with the private sector to reduce emissions. Private actors have also been increasingly engaged in voluntary action to mitigate climate change, especially if they see it as an alternative for tightening regulations (Lee et al., 2016). However, to ensure that the actions are effective enough, they need motivation from the international climate regime (Hickmann, 2017) or through government regulations (Lee et al., 2016). The climate-change discourse has the power to create collaborations even in less-supportive contexts, although this does not necessarily develop into actual redistribution of power and may even end up reinforcing problematic use of power (Westman and Castán Broto, 2018; Sovacool et al., 2019).

Various voluntary approaches (VAs) have spread through environmental policymaking, adding to the command-and-control approaches (de Vries et al., 2012), including different voluntary programmes and certificates (for example Darnall and Sides, 2008; Lee et al., 2016; van der Heijden, 2020). Voluntary city-to-business networks (CBNs) are one, open-ended way of engaging the private sector to support the climate change mitigation goals of cities. This model is also in use among different city networks, in which cities cooperate and/or promise to take certain steps to mitigate climate change (Kern and Bulkeley, 2009; Bansard et al., 2017). There is a growing literature base on city networks in the context of urban climate governance (Fünfgeld, 2015; Acuto, 2016; Busch et al., 2018; Acuto and Leffel, 2020; Mokhles and Davidson, 2021), and early evidence that they can be successful in lowering emissions, fostering expertise, and providing peer support (Karhinen et al., 2021). However, there are very few studies on CBNs. Here, we study one such network, Climate Partners (CP), started by the city of Helsinki and active in the Helsinki region since 2011.

VAs often contain common goals and rules for participants. For example, a programme or network may be selective about who can join (Haupt and Coppola, 2019; Nielsen and Papin, 2020), requiring that all participants cut their emissions by a certain percentage and report about it in a certain way (Papin, 2019; van der Heijden, 2020). However, formalised networks can adopt a more platform-like approach, open to everyone in the target group (e.g. any city or company) and focus on soft measures, like information sharing or learning from the experiences of others (Haupt and Coppola, 2019; Hickmann, 2017), as well as creating feelings of unity and inspiration (Perkins and Nachmany, 2019).

CBNs, such as CP in Helsinki or others in Stockholm or New York City, work principally as a platform, aiming to keep the participation threshold low. These goals are similar to many city networks that also seek to support climate action by offering members a platform for sharing knowledge, learning from each other, and innovating together (Bulkeley et al., 2003; Busch et al., 2018). However, they differ from those of business-targeting voluntary environmental programmes (VEPs) that aim to self-regulate certain industries (Lee et al., 2016). Knowledge-sharing across different disciplines or actor groups is essential for processes such as social learning in environmental management (Keen et al., 2005). A network can enable this only if members participate actively in network activities. Thus, evaluating participation is a central part of defining the performance of a VA (van der Heijden, 2020).

To be successful, VAs need to solve the regulation dilemma: while joining a network or programme by no means guarantees a commitment to fulfilling promises or reaching goals, too much regulation limits the number of actors willing to participate (Potoski and Prakash, 2004; van der Heijden, 2020). However, if a VA has too weak a structure, the members may end up performing worse than non-members (Darnall and Sides, 2008). As stated, CP allows a lot of freedom to its members. Since the network has no obligatory reporting system and the coordinators do not carry out evaluations, the reliance is on the voluntary self-reporting of the members when evaluating the performance of the network.

Apart from participation, the VA literature finds that there are general direct outcomes that are relevant for defining the performance. These include the change in the behaviour of the members in compliance with the rules of the VA and the overall impact of the VA on the problem it seeks to address (Darnall and Sides, 2008; Gunningham, 2009; de Vries et al., 2012; van der Heijden, 2020).

CP explicitly states that it will increase collaboration, innovation, and learning among the members[1]. If these processes are to happen, network events should bring members together and induce genuine collaboration between them. When joining CP, members are required to make a climate-change mitigation commitment that exceeds the requirements of the current legislation and supports the climate goals of the city of Helsinki.[1] However, in practice, very different goals are accepted. The members are encouraged to report their achievements, but participation in reporting is voluntary.

To examine how CBNs contribute to urban climate governance, we pose the following questions:

- How actively do members participate in CP between 2011 and 2018?
- Does CP bring together companies from different business fields?
- What is the self-reported performance of the members in goal setting, reporting, and achieving their climate-change mitigation goals between 2011 and 2018?
- Is frequent participation in CP events associated with high scores on the self-reported mitigation performance index?

Participation in events creates a connection structure between network members. We study this structure with methods of network science (graph theory) and a quantitative performance index. For the sake of clarity, we use the term ‘graph’ when referring to a network as a unit of analysis. The term ‘network’ refers to the organisation. We share our analysis tools as Python code via GitHub, making it easy to apply our analysis to other CBNs and compare them to CP.

Our results show a moderate correlation between event participation activity and a higher self-reported performance index. CP manages to bring different companies together but has difficulties in keeping them committed to network activities. Similarly, while

[1] Climate Partners web page: https://helsinginilmastoteot.fi/en/climate-partners/

some members report actively and set and reach ambitious goals, such as carbon neutrality, others do not report at all. Many members do not report any emission decrease and promise actions they would most probably take without the network membership. We discuss the meaning of these findings for the overall impact the network has in supporting the goals of the city of Helsinki, and how networking could be further developed and how the methods we present may open new horizons in studying urban climate governance.

## 2. Materials and methods

### 2.1. The Climate Partners network

We use CP as a sample case here, since it is already an established climate action network for big companies[1]. CP is a local-level network, that is, its aims and activities relate to the Helsinki region, but some members are international companies. Initiated in 2011, the network has held events every year since then. From 2011 to 2018, 93 companies and organisations were listed as CP members in at least one year, although by 2018 some of these companies did not participate in CP activities any longer. However, since there is no official procedure for leaving the network, we consider all companies as CP members, starting from the year they joined. Despite the network being voluntary, a company officially signs a commitment with the assistant major stating their climate goals. While the purpose of the network is to support the climate goals of the city of Helsinki, namely carbon neutrality by 2035, the members define their individual goals themselves. It is recommended that the goals '[s]hould be aimed at improving the current situation and should outweigh the current legislation'.[2] CP's goals aim at supporting climate actions that are also beneficial for the business.

### 2.2. Data

The data consisted of lists of companies or organisations whose representatives had registered for events organized by CP during 2011–2018.[3] For analysing the performance, we used reports and documents produced by the network and its members.

Based on the information provided by CP, we divided the all CP members and event participants into three membership classes. Business members (BMs) are companies that have signed the CP commitment, other members (OMs) are public institutions and non-governmental organisations (NGOs) that have signed the CP commitment, and non-members (NMs) are event participants that have not signed the CP commitment.

We also divided all CP members and event participants into 15 fields (see the supplement Table S1 for details). First, we created the following fields: city of Helsinki (later HKI), other public services, NGOs, and educational institutions. All these belong to the OMs or NMs membership class. Next, we divided the BMs and the remaining NMs into nine business fields (e.g. logistics, consultation, energy etc.) based on the information available on their web pages. We anonymised the data so that every participant was given an alias consisting of its membership class, a code describing its field, and a number that individualises it within its field. We made sure that the fields are general enough, containing more than one company or organisation always. The City of Helsinki Urban Environment Division provided the event participation data on the condition of anonymisation.

The documents describing the goals and actions of the network members are publicly available on the network's website.[4] To analyse the performance, we developed an index that was calculated from CP's yearly reports from 2012 to 2018. Between 2012 and 2017, the members had provided the information to the city of Helsinki, and the CP coordinator compiled the reports. From 2018 onwards, the members independently added their information on CP's webpage.

### 2.3. Time windows

To address CP's temporal evolution, we investigated its bipartite graph structure (see Section 2.4) at two temporal scales: as static and in two-year time windows. In the former approach, we constructed a single bipartite graph using all events and participants from 2011 to 2018. In the latter approach, we divided the period into four time windows of two years each (2011–2012, 2013–2014, 2015–2016, and 2017–2018) and constructed the bipartite graph separately in each window.

To quantify the turnover in participants between time windows, we used the Jaccard index that measures the fraction of shared members of two groups out of all members of these groups. The Jaccard index between groups $A$ and $B$ is defined as.

$$J(A,B) = |A \cap B| / (|A| + |B| - |A \cap B|),$$

where $|X|$ denotes the number of members of group $X$ and the intersection $A \cap B$ contains the shared members of groups $A$ and $B$. The Jaccard index value of one indicates that groups $A$ and $B$ are the same, while the Jaccard index between groups that share no members is zero.

[2] Climate Partners, 'What does the Climate Commitment mean?', on page https://helsinginilmastoteot.fi/ilmastokumppanit/, cited on 29.6.2022

[3] We had to omit two events from the network analysis: one from 2013 and the other from 2017, since the participant data was not available. However, it is unlikely that this would radically affect the results. Probably the respective time windows would be more similar to the years 2015–2016, which is the time window with most events.

[4] Link to the webpage containing the data (in Finnish, link checked 7.7.2022): https://helsinginilmastoteot.fi/ilmastokumppanit/

### 2.4. Bipartite graph construction

A bipartite graph *G(U,V)* is a graph that contains nodes of two different types. The sets $U$ and $V$ are commonly referred to as top and bottom nodes. A link between two nodes $u$ and $v$ is allowed only if they belong to different node types, that is, $u \in U$ and $v \in V$. Bipartite graphs have been used to study, for example, a person's participation in events (Faust et al., 2002); leaders' memberships in company boards (Koskinen and Edling, 2012); editors' collaboration on Wikipedia articles (Jesus et al., 2009); the robustness of design processes, where people collaborate on different activities (Piccolo et al., 2018); the relationship between development assistance organisations, development issues, and the countries receiving the assistance (Coscia et al., 2013); and the structure of scientific publications and authors (Lehmann et al., 2008). For additional details on the possibilities that the bipartite graph approach opens in analysis of many real-world networks, see Latapy et al. (2008).

We constructed a bipartite graph using participants as the top nodes and events as the bottom nodes. Event participation creates a link between a participant and an event. We removed from the graph all CP members that did not participate in any event. Therefore, the graph did not contain any nodes with degree zero.

### 2.5. Graph analysis

Graph theory allows analysing large amounts of data with little manual work. Graph analysis reveals structures that would be hard to capture through other methods. For example, detecting CP member groups that participate in the largest number of events together, that is, form the largest bicliques, would be an arduous task if performed manually. A comparison to null model graphs allows accessing the statistical significance of the graph analysis outcomes.

#### 2.5.1. Graph density

We used graph density as a rough measure of event participation. This measure shows how many of the possible links are actually present in the graph. In a bipartite graph, the number of possible links is $N_U$ x $N_V$ where $N_U$ and $N_V$ are the numbers of the top and bottom nodes. Thus, the density of a bipartite graph is defined as.

$$d = N_L / N_U \text{ x } N_V,$$

where $N_L$ is the number of links in the graph.

#### 2.5.2. Bistars and starness

A clique is a part of a graph that contains a set of nodes connected by all possible links between them. Therefore, a biclique consists of sets of top and bottom nodes so that each top node is connected to each bottom node. A ($N_U$, $N_V$)-biclique contains $N_U$ top nodes and $N_V$ bottom nodes. We detected the maximal bicliques of the CP graph using the approach introduced by Makino and Uno (2004). For further details, please see the supplement S1. We considered participation in more than one event as an indicator of participants' level of engagement to the network. To investigate this, we defined a bistar as ($N_V$, 1)-biclique, where the top nodes have degree 1; note that these bicliques are not maximal. In other words, a bistar contains one event and those who participated only in that event. To detect the bistars, we removed from the ($N_V$, 1)-bicliques those participants that were connected to more than one event. Further, we removed NMs since they often participate only in single events and can therefore artificially increase the starness of the graph.

To measure the level of engagement, we defined the starness of a bipartite graph $G$ as.

$$s(G) = \sum_{N_{stars}} N_i \Big/ N_U,$$

where the summation goes over all bistars of the graph (altogether $N_{stars}$), and $N_i$ is the number of participants in the $i$th bistar.

#### 2.5.3. Diversity analysis

To investigate how efficiently the CP network manages to bring together participants from different fields, we analysed the diversity of the bicliques. Many measures of diversity originate from biology, particularly from the study of biodiversity or genetics (see e.g. Gaggiotti et al., 2018). For quantifying diversity, we used three different measures: richness, effective diversity, and relative diversity.

The richness of a clique indicates the number of different business fields present in the clique. However, it does not indicate the distribution of the fields among participants. In other words, the richness of a clique can be relatively high although a vast majority of the clique's participants were from a single dominant field, if the participants in the remaining minority are from a high enough number of different fields. However, the diversity of such a clique is clearly not optimal for bringing together actors from different fields: participants could still end up interacting with other participants from their own field.

To correct for the above-described drawback of richness, we used effective diversity based on the Gini-Simpson index, $H_{GS}$ (Gini, 1912; Simpson, 1949; Greenberg, 1956; Berger and Parker, 1970). The Gini-Simpson index of a biclique shows the probability of two randomly (with replacement) selected participants to be from different fields. For a biclique $A$ with participants from $N_{fields}$ different fields, the Gini-Simpson index is defined as.

$$H_{GS}(A) = 1 - \sum_{N_{fields}} p_i^2,$$

where the summation goes over all the fields present in the biclique and $p_i$ denotes the fraction of participants from the $i$th field out of all participants of the clique.

Values of the Gini-Simpson index are by definition limited between zero and one; zero corresponds to a biclique with participants from only one field and one corresponds to a maximally diverse biclique. To acquire an integer-valued measure comparable to richness, we transformed the Gini-Simpson index to effective diversity (Hill, 1973; Kimura and Crow, 1964; Jost, 2006) as.

$$D_{eff}(A) = 1/(1 - H_{GS}(A)).$$

Effective diversity shows how many fields there would be in a biclique that has the same number of participants from each field present and the same Gini-Simpson index as biclique *A*. Compared to other diversity measures, $D_{eff}$ gives particular weight for the equal distribution of fields (Hill, 1973; Lande, 1996; Jost, 2006). A higher equality in the distribution of fields increases the probability of interactions between participants from different fields.

The definition of the Gini-Simpson index assumes large population sizes where random selection with replacement unlikely yields picking the same participant twice. Not all bicliques of the CP graph are particularly large, which may lead to underestimating the Gini-Simpson index and therefore the $D_{eff}$. However, this is not a problem in our analysis since we compare the diversities of the CP graph bicliques to a null model with the same biclique size distribution and, thus, similar error in the estimation of the Gini-Simpson index.

The richness of a biclique sets a strict upper boundary for effective diversity. To compensate for the dependency between richness and effective diversity, we defined the relative diversity of biclique *A* as.

$$D_{rel}(A) = D_{eff}(A)/R(A),$$

where *R* denotes richness. $D_{rel}$ shows how close a biclique is to its own maximal $D_{eff}$.

#### 2.5.4. Null model graphs and CDFs

To interpret the obtained starness and diversity values, we compared them to the ones obtained from null model graphs. To build a null model for the starness and field-wise mean degree analysis, we constructed link-shuffled versions of the CP bipartite graph. To this end, we first created an empty bipartite graph with $N_U$ and $N_V$ equal to those of the original graph. Then, we added to this graph $N_L$ links allowing at maximum one link between each pair of top and bottom nodes. This resulted in a random bipartite graph with the same density as the original graph but with different connection structures and therefore different starness.

To evaluate the starness of the original graph, we created 1000 link-shuffled graphs, calculated the starness of each of these graphs, and compared the starness of the original graph to the pooled mean of the starnesses of the random graphs by one-sample *t*-test (SciPy function *ttest_1samp*). Further, we investigated the distribution of the event participation of the top nodes by comparing the cumulative degree distribution functions (CDFs) of the original graph and the link-shuffled null model graphs. At any point *x*, CDF(*x*) indicates the number of top nodes with a degree smaller or equal to *x*, or, in other words, the number of participants that participated in *x* or less events. To construct the CDFs of the null model graphs, we pooled the degrees of the 1000 null model graphs together.

For the diversity analysis, we used field-shuffled graphs as the null model. To obtain a field-shuffled version of the CP bipartite graph, we randomly reassigned each of the top nodes with a new field, retaining the original numbers of the top nodes from each field as well as the connection structure of the original graph. To evaluate the richness, $D_{eff}$, and $D_{rel}$ of the original graph, we constructed 1000 field-shuffled graphs and calculated the mean richness, mean $D_{eff}$, and mean $D_{rel}$ over bicliques in these graphs, and compared the pooled means of these values to the values obtained in the original graph by a one-sample *t*-test.

### 2.6. Reported performance index

To analyse the performance of CP members when it comes to reaching their climate goals, we analysed the openly available yearly reports (see 2.2.). For this purpose, we developed an index that describes the performance of the CP members through seven indicators (see Table 1). Drawing from van der Heijden (2020) and de Vries et al. (2012), we related the indicators to three possible forms of the direct impact of networking: goal setting, reporting, and reaching goals. We define *indicator*, *index*, and *parameter* as agreed in the Organisation for Economic Co-operation and Development (OECD (Organisation for Economic Co-operation and Development), 2002) and as used in academic literature (e.g. Mayer, 2008; Dizdaroglu, 2015). We evaluated the indicator values by coding the yearly reports of the CP converted in Microsoft Word (2016).

We evaluated the indicators separately and then normalised them by their theoretical maximum. Therefore, each indicator received a value between zero and one, and the maximum index for each membership year was seven. Maximum for the index over the observed time was 7 * [membership years], 49 if the member had joined in 2012.[5] To compare the results of different companies and combine them with the network data, we normalised the total index (*x*): *x* / (7 * [membership years]). Members who did not report in any year after joining the network scored zero for that year.

[5] Most reporting companies report goals and progress towards them in the same year. Therefore, even though the network has officially been active from 2012, the index could be fully calculated for that year as well.

**Table 1**
The structure of the performance index (for coding examples, please see the supplement S3).

| Indicator themes | Indicators | Scoring | Explanation |
|---|---|---|---|
| Goal setting | Emission reduction goal | No/unclear = 0<br>Yes:<br>carbon negative = 3<br>carbon neutral = 2<br>decrease = 1<br>+<br>whole company = 1<br>part of company = 0 | The main aim of the network is to support climate change mitigation. Promising emission reduction is a clear indicator of contributing to this, as well as to the carbon neutrality goal of Helsinki. |
| | Other goals supporting the goals of Helsinki | No/unclear = 0<br>Yes = 1 point / following:<br>energy consumption<br>renewable energy<br>sustainable transportation<br>sustainable consumption | The four categories defined based on Helsinki's climate documents:<br>Ilmastoesite (2010),<br>Ilmastotavoitteet (2017),<br>Hiilineutraali Helsinki -toimenpideohjelma (2018) |
| Reporting | Measurability | No/unclear = 0<br>Yes:<br>all goals = 2<br>some goals = 1 | Score is given if the goals are directly measurable or if the company states how it evaluates achieving them. |
| | Reporting set goals | No/unclear = 0<br>Yes:<br>all goals = 2<br>some goals = 1 | If the network supports the climate actions, the companies should advance with the set goals. |
| Impact | Achieving reported goals | No/unclear = 0<br>Yes:<br>all goals better than planned = 4<br>all goals =3<br>all goals, (some) partly = 2<br>some goals/only goal partly = 1 | If the network supports the climate actions, the companies should advance with the set goals. |
| | Absolute emission decrease | No/unclear = 0<br>Yes = 1 | The ultimate goal of mitigation is to decrease the absolute emissions. |
| | Energy consumption decrease | No/unclear = 0<br>Yes = 1 | This does not fully correlate with emissions but is often considered beneficial for mitigation. |

### 2.7. Implementation

For constructing and analysing the bipartite graphs, we used the Python (version 2.7; van Rossum and de Boer, 1991; www.python.org), NetworkX (version 2.1; Hagberg et al., 2008; networkx.github.io), pandas (version 0.22.0; McKinney, 2010; https://pandas.pydata.org/), NumPy (version 1.14.0; Harris et al., 2020; www.numpy.org/), and SciPy (version 1.0.0; Virtanen et al., 2020; www.scipy.org) packages. For visualization, we used the Matplotlib package (version 2.1.2; Hunter, 2007; matplotlib.org/). All analysis code, together with a Jupyter notebook showing an example of the analysis pipeline, is available at https://github.com/onerva-korhonen/climate-companions-bipartite.

## 3. Results and discussion

On average, CP organized 4.5 events per time window, ranging from two (2011−2012) to seven events (2015–2016); see Table 2 for more information. The events attracted on average 28.61 BMs, OMs, and NMs per event, ranging from a minimum of 9 participants to a maximum of 57 participants (excluding the HKI members coordinating the network). On average, the participants participated in 4.41 events, ranging from a minimum of 1 event to a maximum of 14 events (this calculation did not include the HKI members, the CP members that participated in no events, or the NMs that typically participated in only one event). Of the total 93 CP members, 7 members participated in no event during the period of the study.

In all time windows except 2015–2016, a majority of the participants were BMs. Their number stayed at 30 for the first two time windows and increased to 38 in 2015–2016, which was the time window with the highest number of events. The number of BMs further increased in 2017–2018 although the number of events decreased. The number of OMs doubled from 6 to 12 from 2011–2012 to 2013–2014 and stayed rather stable after that. This difference is probably due to the growth of the network and a majority of new members being BMs. The number of members not participating in any event grew over time windows, both in terms of absolute and relative numbers. The number of NMs was relatively low in the first two time windows but increased about fivefold from 2013–2014 to 2015–2016 (from 12 to 63); in 2015–2016, a majority of all participants were NMs. The number of NMs also stayed high in 2017–2018. Since the NMs typically participated in only one event, a vast majority of all unique participants were NMs.

We quantified the participant turnover between time windows by the Jaccard similarity index. The mean Jaccard index between the consecutive time windows was 0.31 (for details, see supplementary Table S2). In other words, around two thirds of CP event participants changed between consecutive time windows. The main reason for the low Jaccard index value is the high number of NMs;

**Table 2**
Properties of the CP network and the corresponding bipartite graph.

| Year | 2011–2012 | 2013–2014 | 2015–2016 | 2017–2018 | all |
|---|---|---|---|---|---|
| Network properties | | | | | |
| BMs | 30 | 30 | 38 | 54 | 69 |
| OMs | 6 | 12 | 10 | 11 | 17 |
| NMs | 9 | 12 | 63 | 46 | 117 |
| $N_{nonpart}$ | 8 | 8 | 14 | 28 | 7 |
| $N_{events}$ | 2 | 4 | 7 | 5 | 18 |
| $N_{part}$/event[a,b] | 28.00 (23–33) | 24.25 (19–38) | 26.71 (9–57) | 35.00 (9–54) | 28.61 (9–57) |
| $N_{events}$/participant[a,c] | 1.31 (1–2) | 1.98 (1–4) | 2.58 (1–6) | 1.94 (1–5) | 4.41 (1–14) |
| | | | | | |
| Graph properties | | | | | |
| Density[d] | 0.64 (0.67) | 0.46 (0.51) | 0.25 (0.39) | 0.33 (0.41) | 0.15 (0.26) |
| Starness | 0.69 (>0.52)* | 0.40 (>0.28)* | 0.25 (>0.17)* | 0.46 (>0.30)* | 0.24 (>0.04)* |
| Richness[e] | 11.67 (<11.77)* | 10.40 (>8.94)* | 6.35 (>6.04)* | 8.48 (>7.45)* | 6.62 (>5.68)* |
| $D_{eff}$[e] | 9.00 (<9.22)* | 8.61 (>7.24)* | 5.34 (>4.87)* | 6.93 (>6.20)* | 6.10 (>4.96)* |
| $D_{rel}$[e] | 0.78% (<79%)* | 85% (>82%)* | 90% (>86%)* | 86% (>85%)* | 94% (>89%)* |

$N_{nonpart}$ = number of BMs and OMs that did not participate in any event, $N_{events}$ = number of events, $N_{part}$ = number of companies participating in an event.

[a] Mean (min-max).

[b] Excluding HKI participants

[c] Excluding BMs and OMs that did not participate in any event, NMs, and HKI participants.

[d] Density with and (without) NMs.

[e] Mean over all bicliques.

[*] Observed value is different from the mean over the null model graphs, $p << 0.001$.

the mean Jaccard index calculated without the NMs was 0.51. New members lower the value of the Jaccard index: a member rarely participates in events before joining, so if any new members have joined between two windows, the participant overlap between these windows is smaller than one.

### *3.1. How actively do members participate in CP?*

A company can participate in CP through event participation and public reporting. We analysed the first using the graph analysis and the second through related documents. Overall, some members participate quite actively, some do not participate at all, and some fall in between.

The graph visualization of event participation is characterized by bistars, or events surrounded by participants that joined only that event (Fig. 1). This structure is visible both in the graphs constructed in the two-year time windows (Fig. 1 C, D) and, although to a lesser extent, in the graph constructed over the whole period of investigation (Fig. 1 A, B). The presence of bistars is partially explained by the large number of NMs (indicated by a diamond) but remains visible even after removing the NMs from the visualization (Fig. 1 B, D).

We investigated the event participation further with graph density and starness (see Sections 2.5.1 and 2.5.2 for methodological details). Density and starness open two different viewpoints on event participation, with density concentrating more on the optimal case of very high participation and starness targeting participation in single events only.

The average graph density over time windows is 0.42 (for details on developments over time, see Table 2), indicating that a little less than half of all potential participant-event pairs was present. The large number of NMs decreased the density; the average density increased to 0.50 when we excluded NMs. Density decreased with the increasing number of events, probably reflecting companies' limited time resources. Besides, in time windows with more events, some events target only a certain part of the CP members, so that a lower density may be desired in these windows. For example, climate-smart building (2016) or investing strategies (2018) are topics that are probably not equally interesting to all members.

The density of the graph constructed over the whole period of investigation was notably lower than the average density over time windows (0.15 with NMs, 0.26 without NMs). This shows that although BMs and OMs participate in events actively inside single time windows, only a fraction of them participates actively in multiple windows.

The average starness over the time windows was 0.45 (for details, see Table 2). This means that within each window, almost half of the BMs and OMs that participated in any event, participated only in a single event (NMs were excluded). The starness of the graph constructed over the whole period was lower than the average starness over windows, that is, 0.24. This indicates that some members relatively inactive at the scale of two-year windows return to participate in CP activities in later time windows. However, it remains questionable if the participation frequency of less than one event per year is enough for reaching CP aims.

Similar to density, starness decreased with the increasing number of events. When more events are available, companies most probably find several events that both match their interests and fit their schedules, especially if the events are diverse, for example, ranging from more general annual seminars targeting all CP members to workshops focusing on a certain topic.

The starness of the CP graph was significantly higher than in the link-shuffled null model in all time windows as well as over the

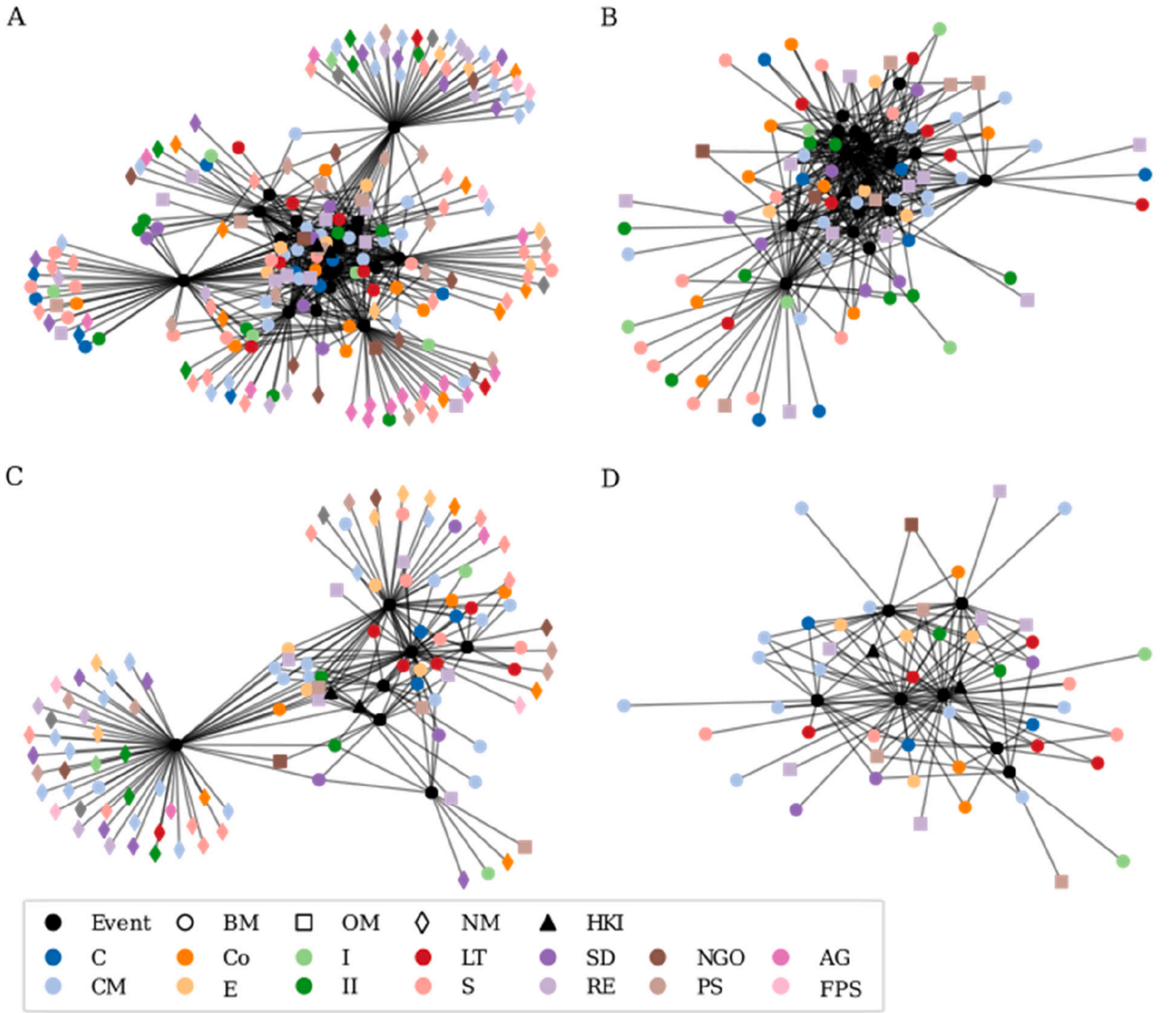


**Fig. 1.** The CP bipartite graph is characterized by bistars of one event and participants that participated only in this event. Bistars are present, although smaller, even after removing NM nodes. A–B) The graph constructed over the whole period 2011–2018 with (A) and without (B) NMs. C-D) The graph constructed in the 2015–2016 window with (C) and without (D) NMs. We considered this time window representative, since it does not lack any event, nor is the first time window where the network was set up. [This should be printed with colours].

whole period of investigation (see Table 2 and Section 2.5.4 for details). This indicates that the event participation of the CP members is distributed differently than expected by knowing only the total number of participants. As expected, the cumulative degree distribution functions (CDFs) show that the CP graph has more participants of degree one than the null model graphs (Fig. 2; for details see Section 2.5.4).

Since the null model graphs contain the same number of links, or participant-event pairs, as the CP graph, the inactivity of the degree one participants must be compensated by increased activity from other participants. This is most clearly visible in the graph constructed over the entire period of the investigation. The two CDF curves intersect at around degree five, indicating that the CP and null model graphs have the same fraction of participants of degree five or smaller and, thus, the null model graphs have more participants of degrees two to four. For degrees greater than five, the CDF of the null model graphs is larger than that of the CP graph and saturates at around degree eight, indicating that the null model graphs have few participants with a degree higher than eight. Meanwhile, the CDF of the CP graph increases steadily till the largest degree of the graph, 14, indicating that the CP graph contains more participants of the highest degrees than the null model graphs. Similarly, although less clear, behaviour is visible also in years 2013–2014 and 2017–2018. In years 2015–2016, the CP graph contains around the same fraction of high-degree participants as the null model graphs and more participants of degree four. The high number of events and low starness in this window may explain the different behaviour of the CDFs.

The first time window, 2011–2012, differs from the other windows in terms of CDF (for the plot, see the supplementary Fig. S2).

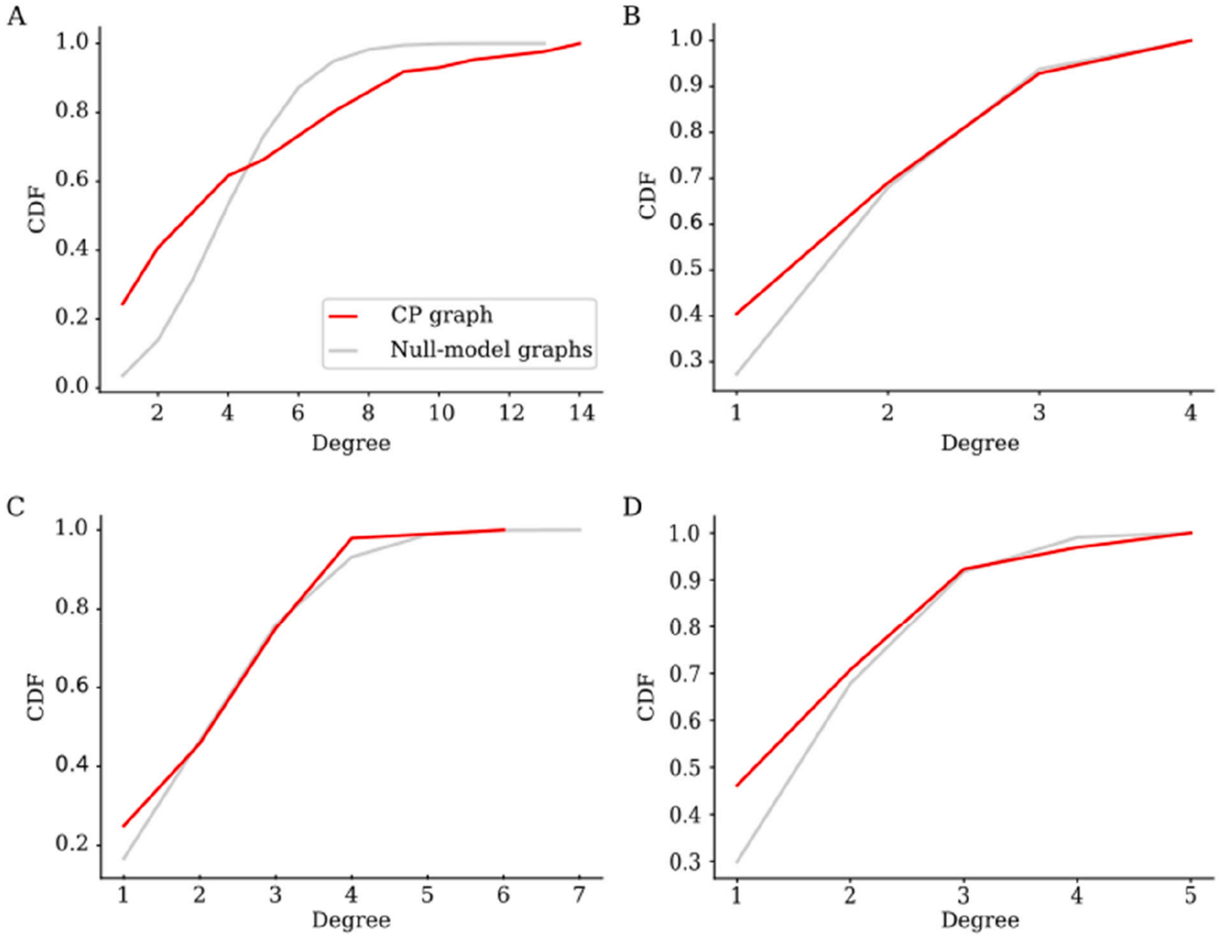


**Fig. 2.** The CP graph has more degree one and high-degree participants than the null model graphs. CDFs of the CP graph and null model graphs calculated over the entire period (A) and in two-year time windows (B: 2013–2014, C: 2015–2016, D: 2017–2018). For the CDFs calculated in the window 2011–2012, see Fig. S2. For details on interpreting the CDFs, see sections 2.5.4 and 3.1 of the main text.

This window contains only two events, and thus the only available degrees are one and two. Therefore, the higher number of degree one nodes in the CP graph directly indicates a smaller number of degree two nodes.

Event participation is not equally distributed among business fields. In the graph constructed over the entire period, the mean degree of all fields, excluding logistics and transportation and research and education, differed significantly from that of the null model graphs, indicating that event participation depended on the business field (Fig. 3). In particular, members from energy, construction and maintenance, and NGOs participated on average more actively than expected, while members from investing and insurances, and services were particularly inactive.

To summarize, a majority of the members only participated in one event. This applies both when observing individual time windows and the whole period. In comparison to the null model, there were also some unexpectedly active members: three members participated in all events after joining the network and some missed only a couple of events. However, the network core formed by these members seems quite small to efficiently support the aims of the network.

When it comes to reporting, the share of members who report their mitigation progress to CP decreases when the network grows, as shown in Table 3. Sometimes a member starts reporting but later stops or lacks one year. In total, 25 members (27%) reported every year since they joined the network, while 28 members (30%) never reported. The remaining 40 members (43%) missed at least one year of reporting.

Many possible reasons exist for not reporting. The members may consider reporting not useful enough or they may fear that reporting insufficient progress harms their interests (Lee et al., 2016). According to the CP coordinator, sometimes the members have a good intention to report, but simply forget to follow through. Reporting to CP is voluntary, and the companies may have other commitments that require reporting as well. CP published a new webpage, with reports from 2018 onwards, in the spring of 2021. Due to this change, members need to upload their reports independently. This may have decreased the number of members reporting in 2018. Overall, according to Lee et al. (2016), public disclosure of performance does not make VAs more attractive to companies, even though it can be rewarding for well-performing ones. Darnall and Sides (2008) found that self-reporting is not an efficient way to

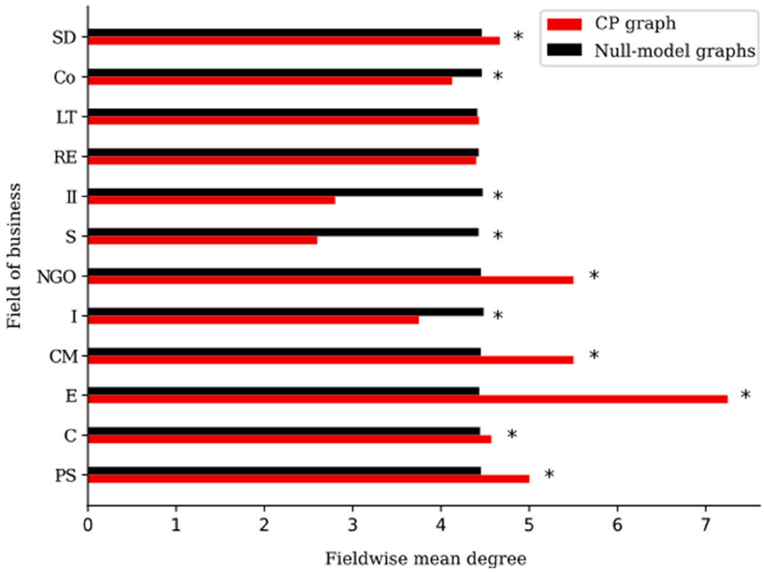


**Fig. 3.** Event participation varies across business fields. The mean degree of participants from different fields in the CP graph (red) and pooled null model graphs (black). *: $p < 0.01$, Bonferroni corrected for multiple comparisons. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 3**
Reporting activity and performance index scores of CP members. $AV_{index}$ is the average index score of all companies that were members in the given year. $AV_{index\_no\_zero}$ is the average index score for all the member companies who reported in the given year.

| Year | Members | Reporting | % | $A_{index}$ | $A_{index\_no\_zero}$ |
|---|---|---|---|---|---|
| 2012 | 36 | 30 | 83% | 2.88 | 3.46 |
| 2013 | 44 | 37 | 84% | 3.26 | 3.87 |
| 2014 | 47 | 37 | 79% | 3.24 | 4.12 |
| 2015 | 57 | 39 | 68% | 2.69 | 3.94 |
| 2016 | 58 | 36 | 62% | 2.35 | 3.79 |
| 2017 | 71 | 35 | 49% | 1.84 | 4.18 |
| 2018 | 93 | 32 | 34% | 1.25 | 3.64 |

support the performance in VAs.

The CP network has successfully grown, meaning that they have managed to keep participation easy and attractive enough for joining (Potoski and Prakash, 2004; van der Heijden, 2020). However, both participation in events and participation in reporting show that most members are not particularly engaged in being active. This may indicate situation in which the network concentrates more on recruiting new members than activating the existing ones. While the will to increase the network is understandable (Potoski and Prakash, 2004), a lack of activity and engagement is potentially problematic for the aims of the network.

### *3.2. Is CP able of bringing together companies from different business fields?*

To evaluate CP's ability to bring together companies from different fields, we investigate the diversity of the CP graph bicliques, or groups of companies co-participating in a set of events. To this end, we used three diversity measures: richness, effective diversity, and relative diversity (for methodological details, see Section 2.5.3).

The mean richness, or the number of business fields present, over bicliques and time windows was 9.23 (for details, see Table 2). Richness decreases with the increasing number of events. When there are more events, there are also more potential bicliques. However, as we noticed above, many companies participate in only a small fraction of events. Therefore, many of these bicliques are small, leaving less space for different business fields. For the same reason, the mean richness over bicliques in the graph constructed over the whole period of investigation was notably smaller than the mean over time windows, that is, 6.62. The richness of the CP graph bicliques is higher than that of the field-shuffled null model graphs in all time windows and over the whole period (for details, see Section 2.5.4). This means that groups of companies participating in several events together contain more business fields than random samples of CP members would contain. In particular, the result indicates that participants from fields less represented in CP participated more actively than expected by their number.

To account for the relative abundance of fields, we calculated the effective diversity (for details, see Section 2.5.3). The mean effective diversity over bicliques and time windows was 7.74 and the mean effective diversity of bicliques in the graph constructed over the whole investigation period was 6.10 (for details, see Table 2). Effective diversity is larger for the CP graph than the null model graphs in all time windows and over the entire period. Similar to richness, effective diversity decreases with the increasing number of events.

To quantify how close the effective diversity of bicliques is to its theoretical maximum, we calculated relative diversity, or the ratio of effective diversity to richness. The mean relative diversity over bicliques and time windows was 85%, while the relative diversity of the graph constructed over the whole period was 94%.

The relative diversity of all time windows and the entire period was higher than that of the null model graphs. This means that the distribution of fields in bicliques is more even than expected by the number of participants from different fields. In practice, the only way to increase the relative diversity further would be to start limiting the number of participants from the most frequent fields of CP. However, this would hardly support the aims of the network.

Further, relative diversity *increases* with the increasing number of events, unlike richness and effective diversity. This means that although event participation varies across business fields, the increased activity is not characteristic to just one or two fields. The small number of highly active participants limits the diversity of the small bicliques of participants co-participating in the largest number of events. In other words, these bicliques are still diverse despite their size.

Based on the biclique analysis, CP does not contain a core of a large number of companies co-participating in many events or any clear structure of participants from the same fields participating in the same events. However, there are small core-like structures of highly active participants. For example, in 2011–2018, a BM from energy co-participated in 14 events with an OM from public services and in 11 events with a BM from consulting; all these 3 members co-participated in 10 events. Likewise, a participant from commerce participated in 11, 10, or 9 events in different combinations with the previously mentioned 3 participants, and all 4 participated together in 8 events.

Based on the three diversity measures, CP is able to create events that attract actors from different fields. However, as seen in the previous section, many members attend only one event. This increases the probability of the connections between members remaining as occasional encounters, which prevents collaboration.

### 3.3. What is the self-reported performance of the members in goal setting, reporting, and achieving goals?

Most members' scores on our self-reported mitigation progress index range from low to mediocre: only 19 members out of the 93 scored 50% or more of their theoretical maximum. On average, the members scored 29% of their theoretical maximums. Out of the 19 companies scoring over 50%, 13 had been CP members from the beginning. However, the two companies with the highest index score were new members: a company from the software and digital services field scored 88% after a 2-year CP membership, and a company from the investing and insurances field scored 71% after a 1-year membership. Out of the companies that scored over 50%, 17 were BMs representing all the 9 business fields in CP, while the two OMs that scored over 50% were from public services.

The average scores per year change in time non-linearly. There is a slight rise between 2012 and 2013, then after 2015, the averages drop (see Table 3). The main reason for this is the growing share of members who do not report and therefore score zero (there are both new members that do not report and members that stop reporting). The average values of members who report do not decrease similarly.

When analysing only the indicators related to emission decrease (P1 = setting emission reduction goal, P6 = decreasing emissions), this result is repeated: the average scores first rise slightly, then drop. In all years, the mean P1 is below 0.25 (Table 4), meaning that many companies do not set any emission decrease target. This may connect to difficulties in measuring emissions. Sometimes the emission decrease goals are set in relation to some variables, like number of staff or sales volume. This in practice means that absolute emissions may grow even if the company achieves its goal.

The values of P6 present the percentage of members who report some emission reduction (Table 4). Even on the best year (2014), this value is below 50%. Apart from actual changes in actions, P6 may drop after 2016 because reporting has changed. For before 2016, there is a table about, for example, changes in emissions and energy consumption for each member, probably indicating that CP asked for this information. The companies rarely make the effort to follow and report their emissions if there is no strong motivation to do so (Hickmann, 2017), and they may hesitate to report their performance publicly (Lee et al., 2016).

Most members set only moderate goals. Few members aim for carbon neutrality or negativity (using compensations). These members are from the fields of consulting and investing and insurances. Some members formulate their climate commitment in quite

**Table 4**
Average values for indicators P1 and P6. P1 and P6 include all CP members (BMs and OMs), $P1^A$ and $P6^A$ include all but those who never reported, and $P1^B$ and $P6^B$ include only the CP members that reported during the year in question. %P1r shows the percentage of reporting CP members who set some emission decrease goal. The values in bold are the highest of that column.

| Year | P1 | P6 | $P1^A$ | $P6^A$ | $P1^B$ | $P6^B$ | %P1r |
|---|---|---|---|---|---|---|---|
| 2012 | 0.12 | 0.14 | 0.13 | 0.16 | 0.14 | 0.17 | 0.33 |
| 2013 | **0.14** | 0.32 | **0.16** | 0.37 | 0.17 | 0.38 | 0.35 |
| 2014 | 0.13 | **0.34** | 0.15 | **0.39** | 0.17 | **0.43** | 0.38 |
| 2015 | 0.10 | 0.27 | 0.13 | 0.34 | 0.16 | 0.41 | 0.38 |
| 2016 | 0.11 | 0.16 | 0.15 | 0.19 | **0.19** | 0.25 | 0.42 |
| 2017 | 0.11 | 0.13 | 0.13 | 0.16 | 0.21 | 0.26 | **0.45** |
| 2018 | 0.06 | 0.08 | 0.08 | 0.11 | 0.16 | 0.22 | 0.34 |

an abstract manner. For example, a member stated that they will continue moving towards a carbon-neutral society but did not specify what actions they will take. There are many cases in which the members reach their long-term goals years before the target year. In some cases, they then limit their actions to maintain the new and better performance, but do not set goals that are more ambitious.

Increasing energy efficiency is a popular goal, as stated by the coordinator of the network; however, the coordinator points out that it gets harder and harder, as the easiest solutions have already been implemented (personal communication with the CP coordinator, 2017). Other examples of climate commitments included decreasing the need to travel through improved remote work possibilities, changing company cars to electric or hybrid vehicles, improving staff awareness, improving recycling, and decreasing paper consumption. Some companies also promised to participate in common projects such as organising energy-related workshops for school children. While many companies concentrated on their carbon footprint, some highlighted what they call 'carbon handprint', promising that they will help their customers to decrease their emissions. In some cases, they also estimated and reported these emissions.

Overall, as regards participation, the performance of a majority of the members is quite mediocre, while some members were very ambitious. Best performers come from different business fields, indicating that ambition, or lack of it, is not connected to special characteristics of the business fields. Generally, the performance does not improve in time. The lack of ambitiousness in goal setting may be connected to the fear of not completing public promises (Lee et al., 2016). Another possible explanation is that a majority of BMs would need stronger external pressure to set bolder goals (Hickmann, 2017; Lee et al., 2016). Darnall and Sides (2008) found that participants of VEPs relying on self-reporting perform significantly worse than non-members.

### *3.4. Do members actively participating in events also have the highest self-reported performance index?*

There is a moderate positive correlation ($r = 0.39$, $p < 0.001$) between active event participation and higher index values for BMs (Fig. 4).[6] However, this correlation does not necessarily indicate a causal connection. There may be variables that make certain companies generally more active in climate change mitigation than others, thus explaining both high event participation and high index scores. For example, these companies may have an active environmental management staff. They may also participate in some other initiative that requires reporting, leading to synergies, as they can submit the same reports to CP. These reasons should be addressed in future research focusing on CP members, combining statistical analysis with qualitative analysis of interviews conducted with as many members as possible.

Some members participate rarely or not at all in the events and score zero or less than 20% in the index. Further, some members score zero in the performance index but participate in events, among them is an OM that participates in all possible events. However, because of the lack of reporting, we do not know if they are making progress. There are also members that rarely participate in events but score high (over 50% of their respective maximum) in the index. These members potentially have something to offer to other members if the network coordinators can motivate them to participate. Focusing more on these groups can increase the overall impact of the network. It would activate the laggards and increase the pool of best practices shared, either by increased reporting or by increased event participation.

CP seems to be facing a regulation dilemma (Potoski and Prakash, 2004): they seek to keep the participation threshold low, but then the network does not push the members to be active and adopt ambitious goals. As a result, some companies present very ambitious goals, such as carbon negativity, while others limit their aims at the level of changing light bulbs or decreasing the use of printing paper. In some cases, a member promises to continue offering services or products that support climate change mitigation, meaning that they simply promise to keep up with their business. While this can be beneficial for climate mitigation, one may ask if giving this kind of promise to the network creates any additional benefit, considering that the company most probably tries to continue its business independent of network membership.

However, to avoid the other end of the regulation dilemma, the solution should not be simply adding regulations in the form of obligatory reporting or strict pre-determined goals. Cortes Berrueta and van der Heijden (2021) found that cities prefer voluntary programmes that do not require any specific impact. One option is to offer more guidance for making commitments, for example, giving concrete examples of commitments that support the climate action of Helsinki, as the current guidelines are extremely vague. Moreover, the city could set loose requirements for commitments, for example, that the commitment has to pertain to decreasing the emissions of the member (but any decrease counts) or that the members have to explain how they follow their progress related to their commitments.

Apart from the rules, the rewards explain the successful performance of a VA (Potoski and Prakash, 2004). Currently, CP primarily offers its members the networking platform and some visibility. Offering better rewards, such as access to relevant information or resources, could motivate the companies to be members, even if the rules get stricter. A network with relatively strict rules can be attractive, if it offers benefits that are remarkable enough (Lee et al., 2016; Nielsen and Papin, 2020). One clear benefit may be better than several benefits (Cortes Berrueta and van der Heijden, 2021). Further research, for example, by interviewing the members of CP and other CBNs, would help us understand the benefits that best motivate the companies to join and stay active.

[6] For OMs, there was no significant correlation between event participation and the performance index ($r = 0.04$, $p = 0.89$).

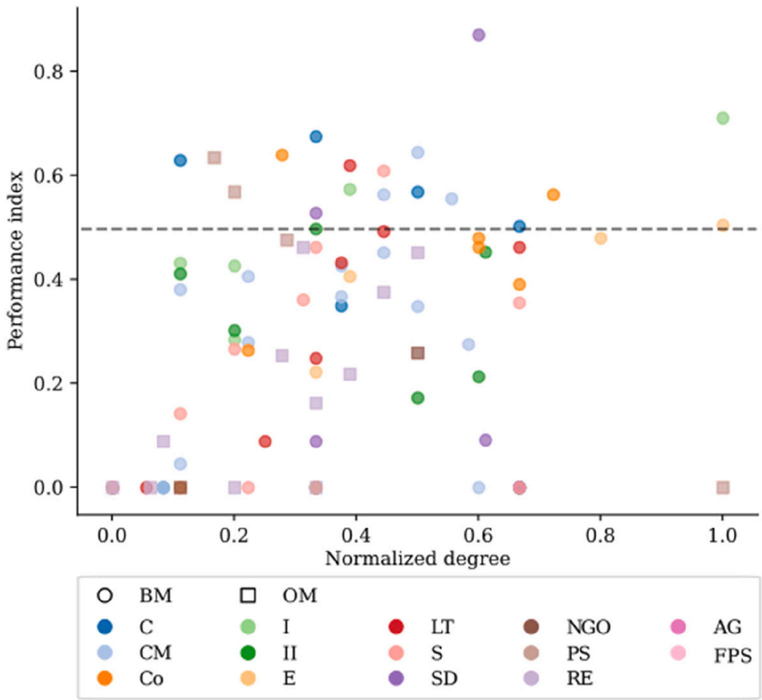


**Fig. 4.** Companies' self-reported performance is, to some extent, connected to their event participation. Values of the performance index calculated over the entire period as a function of degree normalised by the total number of events in each company's membership years. The dashed line shows the performance index value of 50%. [This should be printed with colours.]

### 3.5. Limitations

The main limitations of our study relate to the self-reported nature of the performance index, its inability to separate the impact of CP membership from the impact of other commitments, and the focus on the direct impacts of just the network. Based on current data, we cannot separate the impact of CP membership from the impacts of the members' other commitments. It is clear from the reports that the members do combine their commitments; for example, including in their CP reports energy efficiency projects demanded by another organisation. The overall impact of different commitments and motivations for several memberships is an interesting topic for future research.

As the performance index is based on self-reporting, mistakes and ambiguity in some reports limit their reliability when evaluating the impacts of the network. The form of reporting varies over the years. For example, in some cases the companies may have reduced their emissions and/or energy consumption, but do not mention it in their report, therefore getting a lower index value.

Here, we focus on the direct impacts of the network. CP may have important indirect impacts as well, such as spill-over effects or policy lessons (Darnall and Sides, 2008; de Vries et al., 2012). However, since our current data set does not allow evaluating these, they remain to be analysed in a future study.

## 4. Conclusion

We analysed the CP network as a sample case of CBNs, combining network science with a climate change mitigation performance index based on self-reporting. Our results show that CP is able to bring together participants from different business fields, and there is a positive correlation with event participation and self-reported performance. However, the network struggles with engaging its members in participation in networking events and reporting, and overall, the performance index values are low. Many CP members do not set explicit emission reduction goals nor report absolute emission reductions.

Clarifying the goals and rules of the network may help with these shortcomings. However, the network should, at the same time, offer the members some additional value to keep them motivated to participate. Based on the case of CP, CBNs hold the potential for contributing to urban climate governance. However, stronger motivation and regulation is needed to ensure that the contribution leads to significant and long-lasting mitigation results. Future research is needed to assess the extent to which these results are generalizable to other CBNs. We share the analysis tools used in this article to enable both repeating our analysis with similar data from other networks and developing future research that builds on this analysis.

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## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.uclim.2022.101250.

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