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The Advocacy Coalition Index: A new approach for identifying advocacy coalitions

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Abstract

Policy scholars have increasingly focused on collaborative and competitive relationships between stakeholder coalitions. The Advocacy Coalition Framework (ACF) in particular has directed scholarly attention toward such relationships. The ACF defines advocacy coalitions as groups of actors who share beliefs and coordinate their action. However, previous research has been inconsistent in defining and measuring coalitions, which has hampered comparative research and theory building. We present a method called the Advocacy Coalition Index, which measures belief similarity and the coordination of action in a manner that makes it possible to assess the extent to which advocacy coalitions are found in policy subsystems, whether subgroups resemble coalitions, and how individual actors contribute to coalition formation. The index provides a standardized method for identifying coalitions that can be applied to comparative research. To illustrate the effectiveness of the index, we analyze two climate change policy subsystems, namely Finland and Sweden, which have been shown to differ in terms of the association of belief similarity with coordination. We demonstrate that the index performs well in identifying the different types of subsystems, coalitions, and actors that contribute the most to coalition formation, as well as those involved in cross-coalition brokerage.

KEYWORDS

Advocacy Coalition Framework, Advocacy Coalition Index, belief homophily, brokerage, climate change policy, policy subsystems, social network analysis

INTRODUCTION

Political actors are rarely able to impose their will on others by acting alone. The need to coordinate political action with other actors gives rise to the phenomenon of coalition politics. According to Weible et al. (2016, p. 1), coalition politics results when people or organizations "mobilize and coordinate with others who share their beliefs about what government should or should not do on an issue."

The Advocacy Coalition Framework (ACF) is one of the most prominent theoretical frameworks in relation to coalition politics and public policy in general, with hundreds of empirical applications, initially in the US (e.g., Henry et al., 2011; Weible, 2006) and more recently in Europe (e.g., Ingold, 2011; Nohrstedt, 2009) and elsewhere (Henry et al., 2014). ACF scholars have built upon this wealth of empirical studies for further theory development (e.g., Jenkins-Smith et al., 2014; Weible et al., 2019). With its emphasis on coalition formation, the ACF has enabled public policy scholars to understand how political actors engage with one another, with the aim of translating their policy beliefs and positions into public policy.

ACF scholars have employed various methods to identify advocacy coalitions. A basic premise of the ACF is that "actors who hold similar policy core beliefs will act in concert—[...] the first condition of coalition formation is sufficient for the second" (Sabatier, 1998, p. 115). Accordingly, many of the early ACF applications focused on belief similarity and assumed that the coordination of action would automatically follow. After this assumption was critiqued for being unrealistic (Schlager, 1995), many ACF scholars shifted to social network analysis, with the aim of verifying the co-existence of similar policy beliefs and the coordination of action (Sabatier & Weible, 2007). Some ACF studies that apply network analysis first examine coalitions based on the existence of coordination relationships and then analyze whether beliefs are also aligned (Ansell et al., 2009; DeBray et al., 2014; Gronow & Ylä-Anttila, 2019; Ingold, 2011; Ingold & Gschwend, 2014; Ocelík et al., 2019; Sabatier & Weible, 2007; Tindall et al., 2020; Wagner & Ylä-Anttila, 2018). Others have proceeded in the reverse order, first grouping actors in terms of belief similarity and then based on the existence of coordination (Fischer, 2014; Ingold & Gschwend, 2014).

Variation in how coalitions are measured can be perceived as a strength of the framework that affords it considerable empirical applicability (Weible et al., 2019); on the other hand, it may be perceived as a weakness, particularly in light of the increasing calls for comparative studies regarding coalitions (e.g., Ingold & Varone, 2012) and more systematic theory building informed by empirical studies (e.g., Weible et al., 2019). If coalitions are defined and measured differently in each case, then comparing the results of different studies becomes difficult, which also presents obstacles for theory development. For example, a major comparative ACF book concludes that the authors "are unable to draw direct comparisons across the countries about the coalition attributes given the different methodological approaches" (Ingold et al., 2016, p. 253). Drawing theoretical lessons from comparative research thus becomes difficult if there is excessive variance in the methodological approaches used for measuring coalitions. It is therefore necessary to develop "common and complementary measures of coalition coordination across cases" (Ingold et al., 2016, p. 253). In addition, previous analyses have been able to identify that beliefs either are or are not related to coordination of action, but they have failed to determine why this is the case and how different subgroups and actors contribute to this outcome.

The solution we propose in this paper is the Advocacy Coalition Index (ACI). The ACI provides a standardized method of identifying coalitions that can be used for comparative research and theory development based on cross-case comparisons. Furthermore, the ACI makes it possible to assess the extent to which advocacy coalitions exist in subsystems, the degree to which each subgroup within a subsystem fulfils the belief homophily and coordination conditions of the ACF, and how individual actors contribute to coalition formation. The ACI also helps in terms of identifying instances of cross-coalition brokerage, which can often serve as a catalyst for policy change (Ingold & Varone, 2012).

In the next section, we review the theoretical premises and practical methods related to measuring coalitions presented in the literature and argue that it is necessary to improve the existing approaches. We then introduce the ACI, and to illustrate what it can do, we use it to compare the climate change policy subsystems in Finland and Sweden. To conclude, we discuss the index's benefits and limitations in further detail and suggest lines of future research.

POLICY SUBSYSTEMS, COALITIONS, AND KEY ACTORS

The ACF perceives the policy process as a competition among advocacy coalitions, or groups of actors united by shared policy beliefs (Jenkins-Smith et al., 2014, 2017; Sabatier, 1988; Sabatier & Jenkins-Smith, 1999). Advocacy coalitions are thus defined by both belief homophily and coordination; coalitions are groups of actors who share policy beliefs and coordinate their political activities (Sabatier, 1998). Of central importance here are so-called policy core beliefs, which refer to normative values and perceptions of the policy problems at hand. These beliefs are "the primary perceptual filter for actors in a policy subsystem to determine their perceived allies and opponents" (Weible & Sabatier, 2005, p. 183). The coordination of action is defined by the ACF as "some degree of working together to achieve similar policy objectives" (Sabatier & Weible, 2007, p. 196). Weible et al. (2019) contend that a *minimal* condition for coalitions is that actors share beliefs. Thus, groups characterized by mere belief similarity among actors can be described as coalitions (or "disconnected coalitions" according to Weible), but true advocacy coalitions also coordinate their actions (Weible et al., 2019).

According to the ACF, once policy actors observe that their opponents are beginning to pool resources and form alliances, they also begin seeking allies because "to remain without allies is to invite a defeat" (Sabatier, 1988, p. 140). This perceived need to form alliances is further strengthened by the devil shift, defined as the tendency to perceive one's opponents as being more hostile and powerful than they are (Sabatier, 1988, p. 140; Sabatier et al., 1987). This tendency reinforces the original impulse to assemble into coalitions, which can, in principle, precipitate a situation in which every policy actor is tied to an advocacy coalition.

After the original versions of the ACF were criticized for making unrealistic assumptions that coordination of action would invariably follow from belief similarity (Schlager, 1995), many scholars reacted by turning to network data, hoping that it would make it possible to verify that advocacy coalitions do exist in the sense that they coordinate their actions (Sabatier & Weible, 2007). These network studies have since proven that belief similarity is often associated with the coordination of action (Henry, 2011; Henry et al., 2011; Leifeld & Schneider, 2012; Matti & Sandström, 2011, 2013; Weible & Sabatier, 2005). However, coordination does not always follow from belief similarity, which is why Fischer (2014, pp. 351–52) asserted that direct collaboration may be too rigid a criterion for the existence of coalitions. Other studies have proceeded in the reverse order, beginning with the coordination criterion and then analyzing belief similarity (Ansell et al., 2009; Gronow & Ylä-Anttila, 2019). While these analyses have been able to determine that beliefs either are or are not related to coordination of action, they have struggled to illustrate why this is the case and how different subgroups and actors contribute to the outcome.

Originally, the ACF was developed in the US, but since then, it has been applied in other contexts. In these new contexts, researchers have often found that belief similarity is not always associated with collaboration. Scholars have interpreted these findings by positing that when a policy subsystem is consensual, the role of belief homophily is less pronounced (Gronow et al., 2020). ACF scholars have acknowledged that different types of policy subsystems exist based on the overall mode of interaction among the policy actors. According to Weible (2008), adversarial subsystems are the bread and butter of ACF, but other forms of subsystems are also possible. Subsystems may also be unitary, in which case the subsystem comes down to a single, dominating coalition, or cooperative when different coalitions exist but actors coordinate their actions across coalition lines as well. However, previous research has offered no clear guidelines regarding how to identify different types of subsystems. Our index is helpful because it evaluates the nature of the subsystem on the basis of the extent to which actors coordinate their actions within and across coalition lines. In adversarial subsystems, coordination mainly takes place within coalitions, whereas in cooperative subsystems, coordination tends to extend across coalition lines as well.

The ACF has also categorized different types of coalitions. According to Weible et al. (2019), an adversarial coalition is the ideal-typical advocacy coalition because its members exclusively collaborate with like-minded actors. In contrast, members of cooperative coalitions also collaborate with actors whose beliefs differ from their own. These two coalition types suggest a direct connection with the typology of adversarial and cooperative policy subsystems. Adversarial coalitions exist more often in adversarial policy subsystems, and cooperative coalitions naturally exist more often in cooperative subsystems. However, it is also possible that various types of coalitions coexist in a single subsystem, as our analysis will demonstrate. As a third type, Weible et al. (2019) mention disconnected coalitions, wherein actors share beliefs but act against ACF assumptions in that they do not coordinate their actions despite belief similarity. Ingold (2011) suggests that there can also be intermediate groups, wherein actors form ties with those who do *not* hold similar beliefs. This type challenges ACF theory (Koebele, 2019) because belief homophily does not explain the logic behind the existence of this group. However, previous studies (Ingold, 2011; Ocelík et al., 2019; Satoh, 2014) suggest that such groups exist rather frequently.

There are several possible functions for intermediate groups. If they are connected to several advocacy coalitions, they (or some of their members) can serve as brokers in the policy process (Ingold, 2011, p. 450; Satoh, 2014). Brokers are also typically more moderate in their beliefs than are actual coalition members. An analysis of brokerage in the context of the ACF is important because by mediating between opposing coalitions, brokers make compromises possible (Sabatier, 1988). In the ACF context, brokerage is thus, first and foremost, a phenomenon in which an actor brokers the connections between coalitions (Ingold & Varone, 2012). However, no clear-cut definitions and methods exist for identifying brokers. The Advocacy Coalition Index can be used to identify the aspect of brokerage that is most important from a coalition perspective, namely the fact that brokers mediate the connections between coalitions not between any individual actors. In addition, while some actors may not act according to ACF assumptions, so-called principal coalition members may still do so (Weible, 2008). These actors can also be identified by the ACI. Furthermore, the ACI measures the extent to which each subgroup in a policy subsystem conforms to ACF expectations and, thus, the extent to which coalitions in the real world correspond to the coalitions of the ACF. Finally, as discussed above, ACI can be calculated at the subsystem level so that entire subsystems can be compared to assess the role of advocacy coalitions in policy processes in each case. Next, we explain how each of these features of the index work in more detail.

THE ADVOCACY COALITION INDEX

Identifying coalitions

The ACI is a combined measure of beliefs and collaboration relationships in line with ACF assumptions. Data that include information regarding the policy beliefs of each actor and the relationships that an actor forms with other actors are thus needed. One method of obtaining such data involves surveys with questions concerning beliefs and collaboration, but such information can also be coded from policy documents, press releases, and other materials.

The basic unit of observation is the relationship, namely the existence or the nonexistence of a tie between two actors. We first postulate an ideal type of coordination network in a policy subsystem based on the ACF assumption that like-minded actors tend to coordinate their actions, thus establishing what are called *homophilous ties*. In the extreme case, all like-minded actors collaborate, whereas no connections are forged between actors who hold diverging beliefs. This is a theoretical ideal, and we do not imply that coalitions would ever entirely fulfill these criteria (see also Weible et al., 2019). We use the term ideal-typical coalition to describe a Weberian ideal type that fulfills the ACF's twin theoretical criteria for a coalition and can be used to understand real-life coalitions by comparing them to this ideal. We do not claim that such a coalition would be ideal in the sense that it would, for example, be the most efficient possible coalition for achieving policy goals. Much like many other indicators (e.g., Pearson's correlation), the ideal-typical constellation is not an empirically probable one but a theoretically possible, extreme one. By demarcating a theoretically ideal condition, indicators measure the degree of divergence of empirical results from this idea.

Divergence from the ideal-typical advocacy coalitions can occur in two ways. First, ties can exist between actors who hold different policy beliefs. The interaction between policy actors who hold diverging beliefs has been discussed in the context of "cross-coalition" interactions (Jenkins-Smith et al., 2014, p. 191; Weible, 2005, p. 473; 2008; Weible et al., 2009). Based on this terminology, we adopt the term *cross-coalition ties*. There are several potential reasons why such cross-coalition ties exist. Some policy actors might strive to be policy brokers who mitigate conflicts between opponents (Ingold & Varone, 2012; Weible et al., 2019, p. 8). In some policy subsystems, cross-coalition interactions may be more common because they can help mitigate the costs, politicization, and implementation failures often associated with adversarial processes (Koebele, 2019, p. 39).

In the second scenario, ties do not exist between like-minded actors and are therefore *missing* relative to the ACF ideal type. Whereas early versions of the advocacy coalition framework implicitly presumed that all coalition members interact, this assumption has been revealed to be unrealistic (Schlager, 1995; Weible, 2008, p. 622). For example, as the number of coalition members increases, coordination within a coalition becomes more costly, and it is more difficult to prevent the occurrence of free riding. Accordingly, group size affects the ability of groups to coordinate and engage in collective action (Olson, 1971). The *missing ties* refer to the situation wherein coordination between like-minded actors is lacking.

The ACI takes the maximum value of 1 when no cross-coalition ties or missing ties exist. In contrast, the ACI takes the minimum value of 0 when all ties exclusively exist between actors who hold different beliefs and all homophilous ties are thus missing. Conceptually, the ACI can be written as follows:

$$\text{ACI} = 1 - (\text{Crosscoalition ties} + \text{Missing ties})$$

A simple example illustrates what the equation means in practice. Imagine a subsystem wherein six actors are either in favor of (coded as 1) or against a policy (coded as 0); for the sake of simplicity, the ties are undirected and binary. The first three actors (A1, A2, and A3) are in favor of a policy, while the remaining three (B1, B2, and B3) are opposed to it. Figure 1a exhibits the ideal-type advocacy coalition situation, aside from the ties between A2 and A3 and ties between A3 and B3. The network data are stored in a conventional adjacency matrix format. Likewise, the actors' belief scores are converted into a matrix called the *policy agreement matrix* by taking the absolute difference of the belief score of a pair of actors and subtracting the obtained difference from 1. The cells in this latter matrix are 1 when a pair of actors hold the same belief and 0 when their beliefs differ.

Next, we take the number in each entry in the policy agreement matrix and the number in each entry in the collaboration adjacency matrix as coordinates in the *tie feature plot* (Figure 1b). The points are located on line y = x, which we call the *ideal advocacy coalition line*, if they adhere to the ACF assumption that coordination only occurs between like-minded actors. In our example, point $\boldsymbol{P}_{\boldsymbol{A}1\boldsymbol{A}2}$, which represents the policy agreement between actors A1 and A2 (x-axis) and the collaboration tie between the same two actors (y-axis), aligns with ACF assumptions because these two actors hold the same beliefs and collaborate. Point $\boldsymbol{P}_{\boldsymbol{A}1\boldsymbol{B}2}$ also aligns with the ACF because actors A1 and B2 hold different beliefs and do not collaborate. Point $\boldsymbol{P}_{\boldsymbol{A}3\boldsymbol{B}3}$, however, is not consistent with the ACF, because a coordination tie exists among actors A3 and B3, who do not share beliefs. This tie, in other words, is a cross-coalition tie. Likewise, point $\boldsymbol{P}_{\boldsymbol{A}2\boldsymbol{A}3}$ diverges from ACF assumptions because a collaboration tie is missing between actors A2 and A3, despite the fact that these two actors do share beliefs. The degree of divergence from the ACF ideal type in the latter two cases can be indexed by measuring the point's distance from the ideal advocacy coalition line.

It's worth noting that the ACI places equal weight on the existence of cross-coalition ties and missing ties, although it could be argued that in theoretical terms the ACF would assume that cross-coalition ties should be rarer than missing ties. One option would therefore involve weighting cross-coalition ties

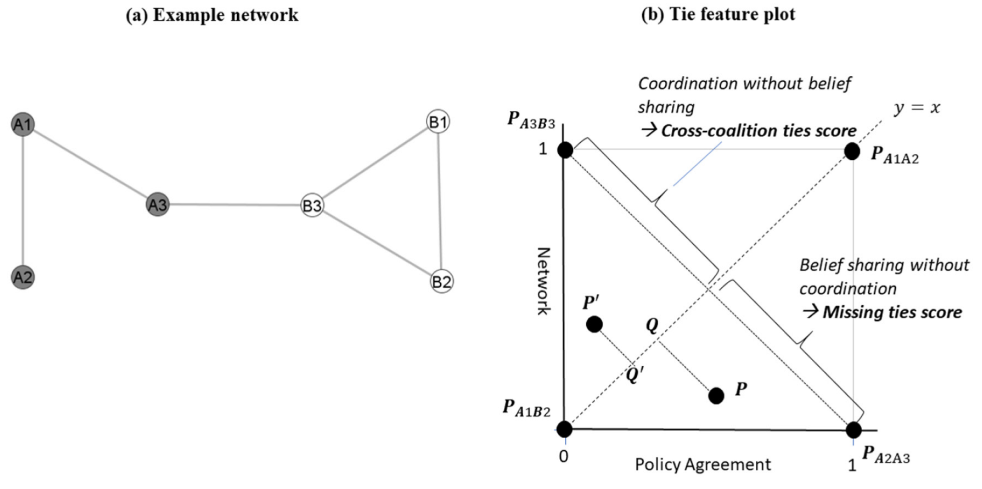

FIGURE 1 Illustration of the idea behind the ACI

in calculating the ACI. However, the actual ratio between missing ties and cross-coalition ties in any subsystem is an empirical question, and it would be difficult to theoretically posit precisely what that weight should be. Thus, rather than weighting, we suggest that interpretations of ACI results should not focus exclusively on the raw value of the index but should account for the ratio of cross-coalition versus missing ties, for which we introduce a measure below.

Until now, we have considered the simplest possible scenario. However, the basic idea can be extended into directed, valued networks with scaled belief attributes, which means that we can consider the direction and strength of collaboration ties as well as degrees of belief. This consideration enables a transition beyond binary classifications (i.e., ties either exist or do not, and beliefs are either similar or different) and offers a realistic description of real-world policy subsystems, in which collaboration is strong or weak, and two actors' beliefs range between absolute similarity and absolute divergence. In addition, multiple types of coordination can be considered. Many surveys, for example, ask about mutual collaboration but also about information exchange and other types of coordination ties between policy actors. With the ACI, these different types of coordination (e.g. collaboration, information exchange) can be compared or combined to better assess the complex phenomenon of coordination. For example, researchers can first create an advocacy coalition matrix for each type of coordination network by setting the common cut-off value of cross-coalition ties, treating this set of advocacy coalition matrices as a multiplex network, and applying clustering techniques such as the generalized Louvain algorithm (Mucha et al., 2010).

The direction of the ties can be considered because our unit of observation is each entry in the matrix. Scaled belief scores can also be considered if the score is standardized such that values vary between 0 and 1. Similarly, valued networks can be handled if the network's value is converted into the range from 0 to 1. However, one should be careful with valued networks and valued policy scores because the standardization method directly affects the final location of the points on the graph. Whether the point is located in the region of the *missing ties score* (e.g., see **P** in Figure 1b) or that of the cross-coalition *ties score* (**P'**) depends upon how the researcher standardizes the scores. Thus, in the complex cases in which both the network ties and policy scores are valued, researchers must examine the location of each point on the graph to determine whether it corresponds with their understanding of the policy subsystem and the position of the actors within it before selecting the final standardization method.

Once the distance from the points in the tie feature plot is determined, a cut-off value for the cross-coalition ties score can be established. Ties above the cut-off value can then be discarded such that the ties in which actors share beliefs and coordinate action to a certain degree are solely left in the network. In our example, we can discard tie A3-B3 and obtain two network components, namely A1-A2-A3 and B1-B2-B3, both of which can be conceptualized as advocacy coalitions. In actual empirical cases, it may not be possible to decompose the network as clearly, because some between-component ties may still exist, depending on the cut-off values. Therefore, in addition to discarding cross-coalition ties, one may consider applying established network subgroup analysis techniques, such as community detection (Blondel et al., 2008) or the factions algorithm (Borgatti et al., 2002), to identify advocacy coalitions. These methods generally force even those actors which would have been better treated as cross-coalition policy actors into coalitions. Our index makes it possible to easily discard cross-coalition ties and identify coalitions that consist of exclusively homophilous ties. Alternatively, it is possible to focus exclusively on cross-coalition ties if the intention is to find potential policy brokers.

Connecting the ACI to the key concepts of the ACF

Thus far, we have elucidated the basic concept of the ACI and how it can be utilized for coalition detection. In addition to this function, what makes our index unique is that the ACI score and its subcomponents — the cross-coalition and missing ties scores — can be calculated at three levels: the actor, the coalition, or the whole-network (i.e. subsystem) level. The denominator of the *missing ties score* indicates how many potential ties among like-minded actors are not actualized. Since it is intuitively easier to think about ties that exist as opposed to focusing on those that are missing, we propose that a useful score for interpreting ACI results is the *homophilous ties score*, calculated as follows:

$$\text{Homophilous ties score} = 1 - \text{Missing ties score}.$$

Both the homophilous ties and the cross-coalition ties score take the value 0 when no ties among like-minded/non-like-minded actors exist and 1 when all potential likeminded/non-like-minded ties are actualized, respectively.

These subcomponents of the ACI are useful for identifying the types of actors, coalitions, and subsystems that have been discussed by the ACF literature. Thus, we believe that the ACI contributes to the literature by offering empirical operationalizations of several theoretical components of the ACF. We present these operationalizations here and demonstrate their use in the empirical section below.

First, actor-level scores for homophilous and cross-coalition ties can be used to identify different actor types discussed in the ACF literature. The ACF assumes that some actors are more central to a coalition than others (Jenkins-Smith et al., 2014, p. 197). To account for this variation, a distinction between *principal* and *auxiliary coalition members* has been made (Jenkins-Smith et al., 2014, p. 197; Larsen et al., 2006; Weible, 2008; Zafonte & Sabatier, 2004). The former actors are central and consistent coalition members, whereas the latter are peripheral and not regularly engaged in coalition-related activity.

The actor-level homophilous ties score is an effective tool for identifying principal and auxiliary coalition members. A high homophilous ties score indicates that an actor has actualized many homophilous ties and is thus a potential principal coalition member. By contrast, a low homophilous ties score indicates that an actor does not have many relationships with like-minded others and may thus be an auxiliary coalition member. For example, in Figure 1, actor A1 has actualized all of their potential homophilous ties and is thus likely to be a principal coalition member, whereas actor A2 has only actualized the other half, making them a likely auxiliary member of their coalition.

The actor-level cross-coalition ties score, on the other hand, can be used to identify *brokers* (Ingold & Varone, 2012) between coalitions. This score indicates how many relationships an actor has with those who do not share the same beliefs. For example, in Figure 1, A3 has a tie with one of three potential opponents; it thus has a cross-coalition ties score of 0.33. The cross-coalition ties score is an apt indicator of brokerage because it directly measures the existence of the ties with actors that differ in terms of their policy beliefs. This transcends most existing measures of brokerage (e.g., betweenness centrality), which assess how brokers mediate connections between actors, irrespective of whether these connections cross coalition lines (cf. Ingold & Varone, 2012).

Second, investigating the ratio of cross-coalition ties and homophilous ties at the coalition level is useful for distinguishing between adversarial, collaborative, and disconnected coalition types and intermediate groups (Weible et al., 2019). For this purpose, we define the *CCH ratio* as the ratio between the cross-coalition ties score and the homophilous ties score:

$$\text{CCH ratio} = \frac{\text{Crosscoalition ties score}}{\text{Homophilous ties score}}$$

The ratio takes the value 0 when there are no cross-coalition ties, 1 when an actor has activated both cross-coalition and homophilous ties evenly, and more than 1 when there are more cross-coalition than homophilous ties. A ratio of less than 1 is expected if actors behave in line with ACF assumptions and predominantly have ties with like-minded actors. However, as demonstrated in the empirical section, some actors and coalitions score higher than 1, reflecting their specific roles in the subsystem.[1.]

At the coalition level, the CCH ratio combined with the homophilous ties score is a useful tool for characterizing the types of coalitions in a two-dimensional diagram. In an *adversarial coalition*, members exclusively collaborate with like-minded actors (Weible et al., 2019). This means that the homophilous ties score is high, and the CCH ratio low because cross-coalition ties are few and far between. Members of cooperative coalitions collaborate not only with like-minded actors but also with actors whose beliefs differ from their own, which should yield a high homophilous ties score and a high CCH ratio. The members of a disconnected coalition share beliefs but do not coordinate their actions despite similar beliefs. They are also inactive in forming ties with their opponents. The last type, intermediate groups, are rather active in forging ties with actors who do not hold similar beliefs (Ingold, 2011) but not active in forging ties with like-minded actors (Figure 2).

The extent to which intermediate actors can be regarded as forming a group depends upon whether there are coordination relationships between them. If such relationships exist, it makes sense to conceptualize these actors as an intermediate group; otherwise, they can be treated as individual intermediary actors.

Lastly, the ACI helps in evaluating the nature of entire policy subsystems. The main forms of policy subsystems identified by Weible (2008) are adversarial, cooperative, and unitary. The first type, the adversarial subsystem, is the ideal type in the ACF context. It is characterized by high intra-coalition and low inter-coalition coordination, which translates into a high homophilous ties score and a low CCH ratio measured at the subsystem level. In the second type, a cooperative subsystem, both inter- and intra-coalition coordination occurs, which is reflected in the subsystem-level ACI as high homophilous ties and CCH ratio scores. The last type, the unitary subsystem, is somewhat challenging for the ACI. Unitary subsystems are characterized by the existence of a single dominant coalition, which manifests in the ACI as a high homophilous ties score and a low CCH ratio, like adversarial subsystems. To

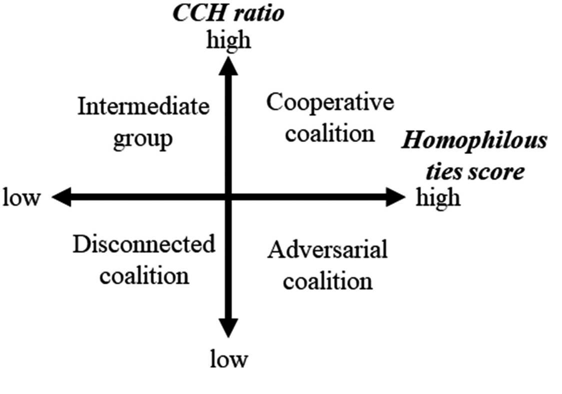

FIGURE 2 Four ideal types of advocacy coalitions

differentiate adversarial and unitary subsystems, researchers thus must interpret the subsystem-level results in combination with coalition level analysis. If there are at least two competing coalitions, the subsystem is adversarial; otherwise, it is unitary.

The formula for calculating the ACI is explained in Appendices A and B (see Supporting Information).[2.] In the empirical section that follows, we demonstrate how the ACI can be used to detect coalitions, understand differences between coalition types and policy subsystems, and identify key actors (e.g. brokers).

THE ACI AND CLIMATE CHANGE POLICY SUBSYSTEMS IN FINLAND AND SWEDEN

Case description and data

As an illustration of how the ACI works in practice, we analyze the climate change policy subsystems of Finland and Sweden. According to the ACF, a subsystem has a functional/substantive and a territorial dimension (Zafonte & Sabatier, 1998). In our example, climate change policy is the substance, and the territories are specific countries. Climate change policy is also done through international negotiations, but the national level is where most emission reduction targets, as well as the concrete policy measures for arriving at these targets, are still established.

Both Finland and Sweden are Nordic corporatist countries, but Sweden is the prime example of the Nordic model of consensual democracy (Lane & Ersson, 2002), whereas the Finnish political system is more conflictual and has been described as a "compulsory consensus" (Arter, 2016). Swedish consensual corporatism has traditionally brought diverse policy actors together to negotiate and reach compromises. This contrast between the countries has been pronounced in the climate policy context. In Sweden, the most influential actors agree regarding the need for ambitious climate change mitigation, and the country's environmental NGOs have been more integrated into the climate change policy subsystem than those in Finland (Gronow et al., 2019). Furthermore, Finnish business representatives, trade unions, and some governmental organizations have, since the 1990s, prioritized economic growth over ambitious climate change mitigation, whereas environmental organizations and their allies have sought to challenge this dominant policy position (Gronow & Ylä-Anttila, 2019; Teräväinen, 2012). Overall, there are reasons to presume that the climate change policy subsystem is more conflictual in Finland than in Sweden. We also know from previous research that the Finnish climate change policy subsystem is more clustered into subgroups based on collaboration and belief similarity (Gronow & Ylä-Anttila, 2019) and that belief homophily explains collaboration in the Finnish but not the Swedish policy subsystem (Gronow et al., 2020). Previous research thus suggests that the Finnish subsystem is closer to the ACF ideal type, in which policy actors primarily collaborate with like-minded actors. This difference between the countries is what we expect the index to demonstrate.

The data, collected in Finland in 2014 and Sweden in 2015, are based on surveys in which the respondents constitute the climate change policy subsystems. The respondents were the most important organizational actors involved in domestic climate policymaking processes in these countries, representing different societal sectors (e.g., NGOs, businesses, governments). The final list of respondents was compiled with the assistance of national climate policy experts. In most cases, the respondents were responsible for either climate policy or environmental policy within their respective organizations. The Finnish and Swedish policy subsystems include 96 and 99 organizations, respectively. The response rates to our online surveys were 86% in Finland and 70% in Sweden.

Data regarding policy beliefs were collected by asking each respondent about their position on 21 different climate policy ideas on a five-point Likert scale (strongly disagree = 1, neutral = 3, strongly agree = 5). Of these 21 items, we selected, with the help of principal component analysis, six that represent policy core beliefs and used them to create a composite variable. The six questions are presented in Table 1. The collaboration data were derived from the question "With which organizations does your

TABLE 1 Descriptive statistics of the policy core beliefs in Finland and Sweden

	Finland		Sweden				
	$n = 82$		$n = 69$			Principal component analysis	
	Mean	SD	Mean	SD	*t*-test	Loadings	Communality
Human activities are important drivers of current climate change.	4.68	0.68	4.81	0.46		0.72	0.52
Climate change science is still too uncertain to be a basis for policy$^{(-)}$	4.55	0.89	4.35	1.12		0.64	0.41
National competitiveness is more important than tackling climate change$^{(-)}$	3.50	1.17	3.71	0.96		0.83	0.68
Securing the national energy supply is more important than reducing emissions$^{(-)}$	3.56	1.08	3.65	0.95		0.81	0.65
My government exerts too much effort to reduce GHG emissions$^{(-)}$	4.16	1.02	4.10	1.10		0.78	0.61
My country should take a leading international role in GHG reductions	3.40	1.34	4.22	1.04	***	0.77	0.59
Principal component score	−0.09	1.08	0.11	0.89			
SS loadings						3.47	
Variance						0.58	

Note: The scale of the items with (−) was reversed.

***$p < 0.001$.

organization collaborate on a regular basis?" To answer this question, the respondents selected from the list of organizations belonging to the policy subsystem; this roster, in other words, is identical to the list of respondents, and the network is binary and directed. The analysis was conducted using R (R Core Team, 2019) and the *sna* (Butts, 2016) and *psych* packages (Revelle, 2018).

The policy core belief score

Table 1 presents the survey questions used for creating the belief score, as well as the descriptive statistics for these items.

Between the two countries, no statistically significant difference was identified among these items, aside from that asking about the country's desirability concerning the adoption of an international role in climate negotiations. These items have a high communality in the principal component analysis, indicating unidimensionality, and we therefore used the principal component score to create a composite variable measuring the pro-climate beliefs of the policy actors. We then normalized this score so that it ranged from 0 to 1. The mean and standard deviation (SD) of this normalized *policy core belief score* are 0.75 (SD = 0.21) in Finland and 0.79 (SD = 0.17) in Sweden. No statistically significant difference was observed in the *policy core belief score* between Finnish and Swedish actors.

Subsystem-level ACI

We start by considering the subsystem-level ACI, which is 0.36 in Finland and 0.24 in Sweden (see Table 2). The higher figure of the Finnish policy subsystem indicates that it is closer to the ideal type of ACF subsystem. As is well known, conventional statistical hypothesis testing is inapplicable in the case of network data, because the distribution of the test statistics is unknown, but various strategies with which to avoid this problem exist. Snijders and Borgatti (1999) propose the vertex bootstrap method for testing statistical significance in a network context. The difference between the subsystem-level ACI for Finland and Sweden is statistically significant ($p < 0.001$), according to the bootstrap-assisted significance test that we performed for this and the following analyses with 1000 samples.

Next, we turn to the sub-scores that constitute the ACI. The homophilous ties score and cross-coalition ties score are 0.23 and 0.19 in Finland, and 0.08 and 0.07 in Sweden, respectively ($p < 0.001$). Interestingly, the ratio of cross-coalition and homophilous ties (CCH ratio) is slightly higher in Sweden (0.85) than in Finland (0.82), but the difference is not statistically significant. Finnish actors have more homophilous ties than their Swedish counterparts and hence the Finnish subsystem is closer to an adversarial subsystem. However, since the CCH ratio is similar in both countries, we do not have sufficient evidence to judge Sweden to be closer to a cooperative subsystem than Finland. However, we also identified a substantial difference in the distribution of the CCH ratio among actors, which will be reported in the last portion of this section.

The subsystem-level ratio of cross-coalition and homophilous ties (CCH ratio) is an appropriate starting point for assessing whether belief homophily is associated with coordination. If this ratio is

TABLE 2 Results for the ACIs in Finnish and Swedish climate change policy subsystems

	Finland	Sweden
ACI	0.36	0.24***
Cross-coalition ties score	0.19	0.07**
Homophilous ties score	0.23	0.08***
CCH ratio	0.82	0.85

**$p < 0.01$; ***$p < 0.001$.

exceptionally high, say, more than 1, belief homophily may not be the primary driver of coalition formation, and coalitions may be based on other factors, such as trust or resources (Henry et al., 2011). In our example, the CCH ratio is relatively high but still less than 1, so it makes sense to proceed to the next step of the analysis.

Coalition-level ACI

The subsystem level analysis revealed, as expected, that the networks contain some ties between actors who do not share beliefs, whereas advocacy coalitions are ideally groups of actors with similar beliefs. Therefore, to identify actual advocacy coalitions, we create a new network in which all ties are exclusively among like-minded actors. In this illustration, we set the common cutoff-value at $\alpha = SD_{\text{policy core}}$. With this operation, ties between actors are solely maintained if the difference between their policy core belief scores is less than one SD of the policy core belief score in each country (other cut-off values are also possible).[3.]

Through this operationalization, the density of the Finnish network diminishes from 0.22 to 0.10, and that of the Swedish network from 0.08 to 0.04. In other words, almost half of the ties were not related to belief similarity at our chosen cut-off value.

We applied the *Walktrap community finding algorithm* (Pons & Latapy, 2005) in the igraph package (Csardi & Nepusz, 2006) for the networks in which only homophilous ties are remaining. This algorithm measures the similarity between nodes based on the probability of the k-random-walk from one node to other nodes. The calculated similarity is then submitted into a clustering method, while the number of communities is determined when the modularity reaches the maximum.

Figure 3 illustrates the subsystems clustered by the identified advocacy coalitions. The Finnish policy subsystem consists of three coalitions (plus an isolated node [F5] and a group with only two members [F4], neither of which we consider coalitions). The Swedish coalition depicts a considerably different structure, in which one coalition (S3) is located in the middle, surrounded by four larger coalitions (S1, S2, S4, S5, S6). Many rather small subgroups and isolates also exist.

In Finland, the homophilous ties score for the subsystem-level is high; accordingly, coalitions are positioned on the right side of the figure. However, coalitions F3 and F1 have a higher CCH ratio than F2. We can therefore interpret F3 and F1 as being cooperative coalitions and F2 as an adversarial coalition. In Sweden, most coalitions have low homophilous ties scores. Two coalitions (S3 and S7) have a particularly high CCH ratio (more than 1). Thus, we may treat S3 and S7 as intermediate groups and all others as disconnected coalitions (Figure 4).

Actor-level ACI

How do these coalition structures come about? To answer this question, we turn to the actor-level ACI. Figure 5 illustrates the homophilous ties score and the CCH ratio (y-axis), as well as the policy core belief scores (x-axis), at the actor level in each country.

In Finland, actors who favor more ambitious climate policies tend to achieve higher homophilous ties scores (Figure 5a1,c1) and a lower CCH ratio (Figure 5b1,d1), which means they coordinate with like-minded actors. Accordingly, dense ties are especially formed among members of Coalition F2, the actors of which believe in ambitious climate policy. In Sweden, the homophilous ties score (Figure 5a2,c2) and the CCH ratio (Figure 5b2,d2) vary among actors and are not associated with their policy beliefs. Many ties exist between coalitions; therefore, no clearly demarcated coalitions exist in the Swedish case.

Specific actors play important roles in each subsystem. In terms of their outgoing ties (i.e., those reported by the actors themselves), in the Finnish case, three actors (*the Social Democratic Party* in Coalition F3, *the Left Alliance* in Coalition F2, and *the Ministry of Economic Affairs and Employment* in Coalition F1) have high homophilous ties scores (Figure 5a1). Thus, they have activated most of their potential ties

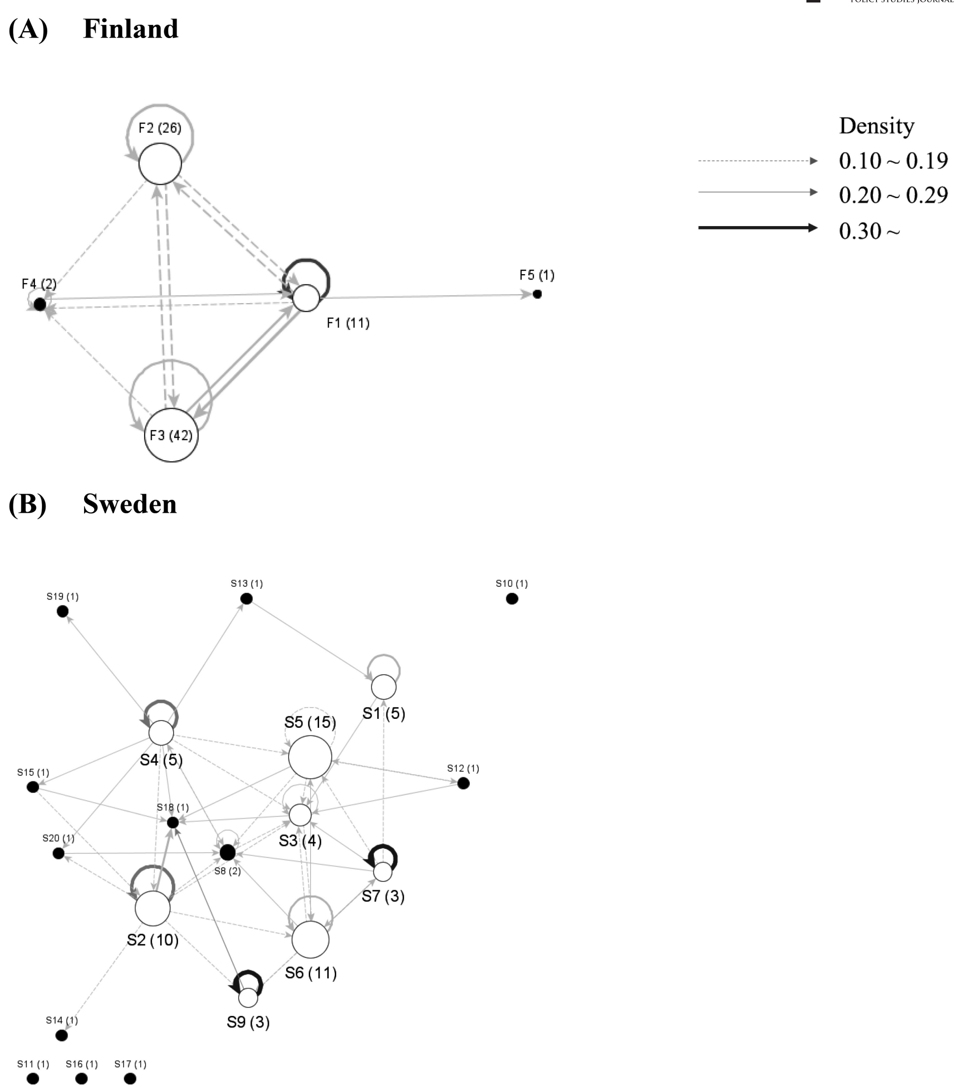

FIGURE 3 Advocacy coalition structure in Finland and Sweden. Each number in parentheses and each node size indicates the number of actors that belong to a coalition. Coalitions with fewer than three members are colored black

with likeminded actors. These actors can be regarded as the principal actors in each coalition. In the Swedish network, no actors possess high homophilous ties scores; rather, several actors from coalitions S2, S3, S5, and S6 have an exceptionally high CCH ratio (Figure 5b2), which means that they are connected with actors with different policy beliefs, thus acting as policy brokers. The result also holds true in terms of incoming ties, with slight modifications; in the Finnish subsystem, the *Ministry of the Environment*, in Coalition F2, has a homophilous ties score as high as that of the *Ministry of Economic Affairs* in Coalition F1 (Figure 5c1). In the Swedish subsystem, the CCH ratio of actors from coalitions S5 and S6 does not stand out, and actors from S1 have a CCH ratio as high as other actors from S3 and S2 (Figure 5d2).

In summation, the Finnish case more closely resembles the ideal-typical coalition structure of the ACF than its Swedish counterpart, specifically because the actors who favor ambitious climate policies tend to form ties exclusively with actors who harbor similar policy beliefs. In Sweden, in contrast, actors connect with other actors who hold diverging policy beliefs.

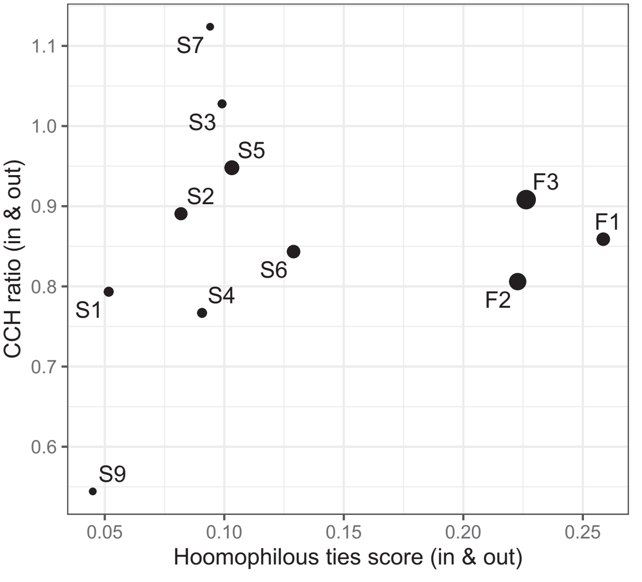

FIGURE 4 Different types of advocacy coalitions in Finland and Sweden. The position of coalitions is based on the average scores of organizations that belong to each coalition. The type of organization can be interpreted by applying the schema illustrated in Figure 2. Coalitions with three or more members are depicted. The size of coalitions represents the number of members

The purpose of our empirical example has been to illustrate the ACI's utility in revealing advocacy coalition structures. Because the same data have been analyzed earlier with different methods, we can also use this example to assess the validity of our index by focusing on the convergence of different measures (cf. Rogers et al., 2018). To do so, we discuss how the coalitions uncovered by means of the index are similar to or different from those found using the same data but different measures also meant to capture advocacy coalitions.

A previous analysis of the same data was performed by first applying the factions algorithm in UCINET (Borgatti et al., 2002) to the coordination data (Gronow et al., 2019). After finding internally dense subgroups based on coordination, the authors analyzed the extent to which these groups shared beliefs. The analysis indicated that the Finnish policy subsystem consists of three main coalitions, but in the Swedish case, it was difficult to find any stable coalition lines due to the extensive coordination of action across the subsystem. In the Swedish case, the analysis did not proceed into analyzing belief similarity, because the authors started with the coordination of action, which did not bring subgroups into existence in Sweden. Even in Finland there were several actors that may be considered cross-coalition brokers, but the method used (the factions algorithm) struggled to find these actors (however, see Ylä-Anttila et al., 2020 for a way to do this). The same data have also been analyzed using exponential random graph models to identify which factors explain the coordination of action (Gronow et al., 2020). In this research, belief similarity explained coordination in Finland but not in Sweden.

Both previous analytical methods and our index thus yielded fairly similar conclusions regarding Finland, but the ACI revealed the roles played by different actors. In addition, the ACI provided a subsystem-level assessment of whether coalitions are likely to be found and indicated the different types of coalitions found in each case. It must be emphasized that the similarity of results provided by our index and other analysis methods was not a preordained conclusion. If there were many cross-coalition ties or very few homophilous ties, a simple clustering algorithm would produce a very different result from the one based on the ACI. For example, if we apply clustering algorithms to the Swedish networks without the ACI procedure, it is highly difficult to interpret the resulting clusters as advocacy coalitions because the clusters contain a mixture of homophilous and heterophilous ties. Where previous analyses had to stop in the case of Sweden, the ACI can identify the reasons why adversarial coalitions (i.e., the

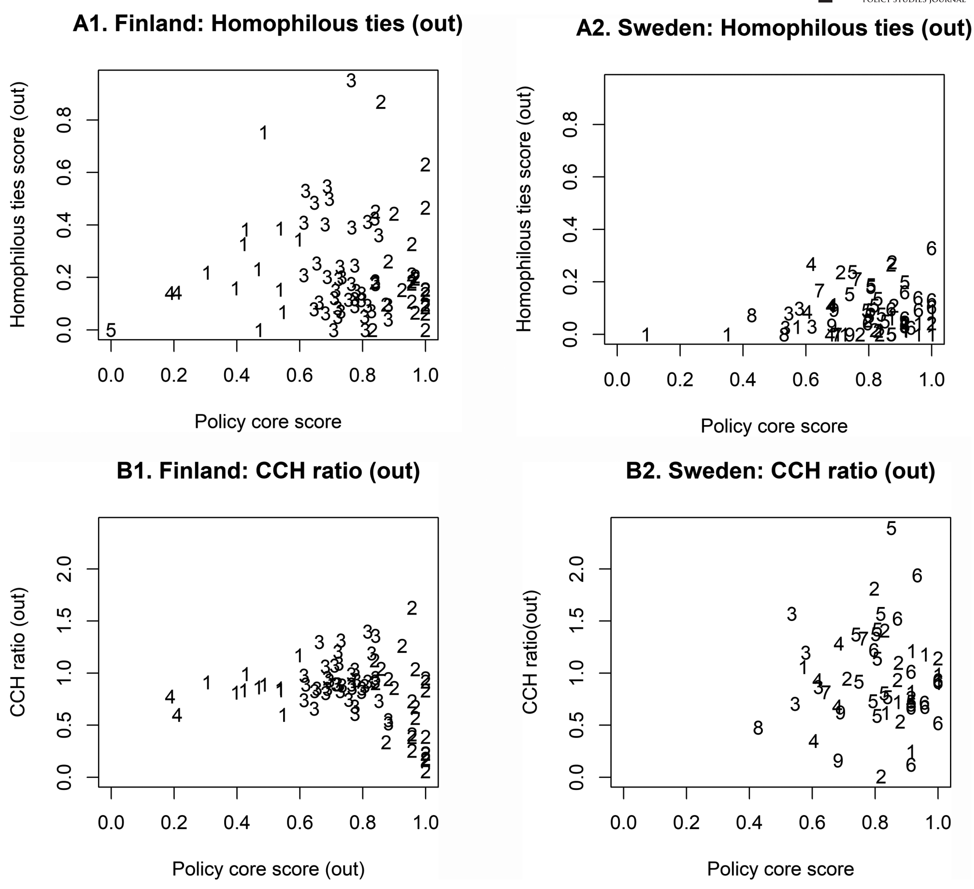

FIGURE 5 ACI score and policy core score. The number indicates the advocacy coalition to which an actor belongs. The coalition number corresponds with Figure 3 and 4. The country specifier ("F" [Finland] and "S" [Sweden]) was omitted

ideal type in the ACF) are not found: There are two intermediate subgroups, and there are many actors that connect with actors with diverging policy beliefs.

DISCUSSION AND CONCLUSION

We opened our paper by noting that previous ACF studies have stressed the twin criteria for the existence of advocacy coalitions—belief similarity and coordinated action—to varying degrees via a myriad of techniques. As Ingold et al. (2016) argue, the lack of a method that could apply these twin criteria to identify advocacy coalitions has hampered the development of comparative research and theory building. While previous research has noted that beliefs either are or are not related to coordination of action, they have not offered clear guidelines for analyzing how different subgroups and actors contribute to the outcome.

We proposed a new index, the ACI, as a potential solution to these problems. The ACI provides a standardized method for identifying coalitions that can be used for comparative research. Calls for more comparative research (e.g., Ingold & Varone, 2012; Weible et al., 2019) are rarely heeded, which is partly due to the absence of standardized analytical tools such as the ACI. The comparison of coalition structures is valuable for theory development in that it helps assess the conditions under which theories and hypotheses hold, as well as the conditions under which they do not.

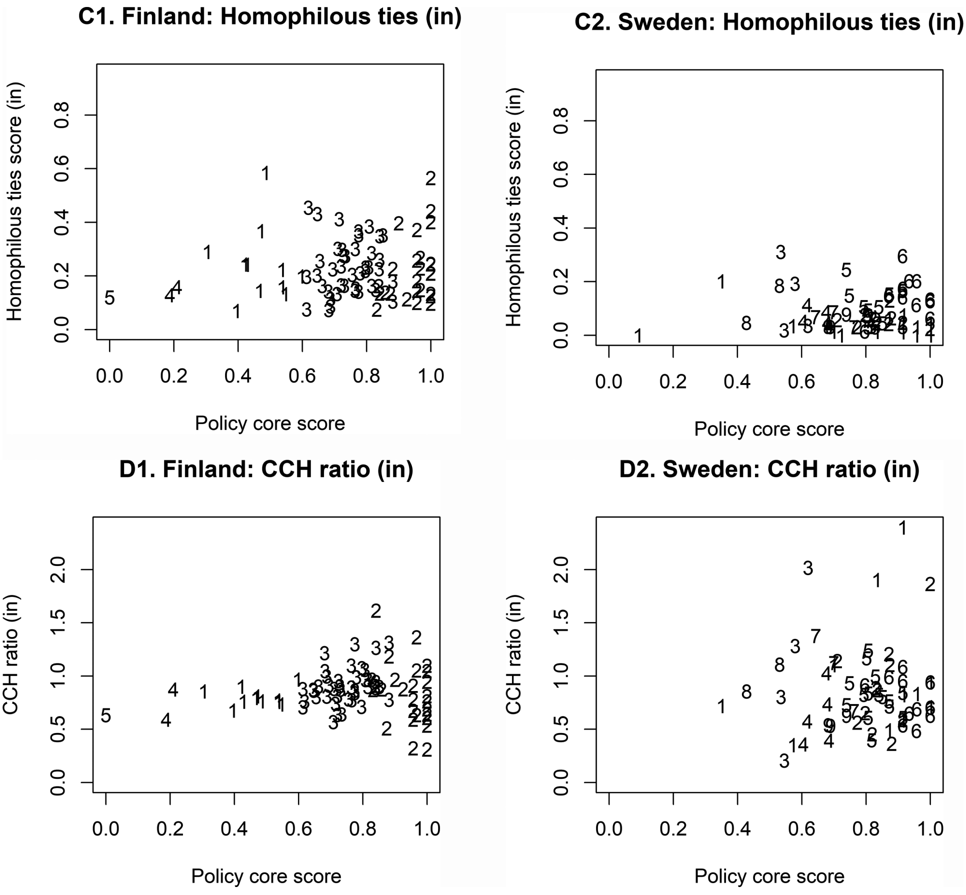

FIGURE 5 (Continued)

The ACI is unique in that it can be calculated at the actor, subgroup (i.e. coalition), or policy subsystem levels. Thus, the index can, for example, determine which subsystems exhibit a general tendency for coordination based on belief homophily—by a simple comparison of two numbers. As we demonstrated, the differences between the climate change policy subsystems in Finland and Sweden can be optimally understood by focusing on all three levels.

The ACI considers differences in the degree of both belief similarity and coordination by analyzing the homophilous ties and the cross-coalition ties scores separately. This makes it possible to empirically indicate which of the coalition types listed by Weible et al. (2019) each coalition most closely resembles: adversarial, cooperative, disconnected, or the fourth logical possibility, which we have called the intermediate group. The ACI thus presents a detailed analysis of the factors that produce these different kinds of coalitions and the reasons for the absence of "expected" coordination (expected according to the ACF ideal-type).

Finally, the cross-coalition ties element of the ACI is helpful in identifying policy brokers (Sabatier, 1988). This feature is important because the analysis of brokerage is underdeveloped in the ACF despite the fact that scholars have argued that brokerage may play an important role in defining policy outcomes when two or more coalitions compete (e.g., Ingold & Varone, 2012). Indicators that social network analysts frequently use to operationalize brokerage solely focus on actors' network positions and do not account for their attributes, such as beliefs. For example, betweenness centrality does not differentiate between whether the ties are formed within a coalition or across coalitions. By contrast, the cross-coalition ties score directly examines the extent to which an actor forms ties with actors whose beliefs are different and thus acts as a broker between coalitions.

The ACI has its limitations, as do all indicators. First, comparing networks in which the proportions of actors holding pro and contra beliefs are considerably dissimilar may prove difficult because the proportions affect the ACI's expected value. By contrast, the effect that a difference in network density exerts on the index is negligible, especially among densities ranging from 0.1 to 0.4, which is the normal range for most empirical networks (See Appendix D for a more detailed discussion).

Second, as with all applications of social network analysis, missing data can be a problem. If an actor who has activated a large proportion of all possible ties with like-minded actors is missing from the data (e.g., due to their non-responsiveness to a survey), it is impossible to find a coalition associated with that actor. A partial remedy to this problem involves checking how results differ if one retains the missing actors in the matrix (by counting their incoming ties) as opposed to eliminating them. By contrast, at the level of subsystems, the ACI is rather robust if the network size is not very small. For example, even if we eliminate the three actors with the highest homophilous ties scores from the Finnish climate change policy subsystem analyzed above, we still achieve a value of 0.34 for the ACI.

Third, comparing subsystems with exceptionally different sizes may cause problems. The more actors there are in a subsystem, the more difficult it is for an actor to form ties with all "available" actors. Hence, it is likely that the cross-coalition ties score and homophilous ties score generally decrease with network size. By contrast, the CCH ratio is comparable across networks of different sizes because this score is the ratio of activated cross-coalition and homophilous ties.

A fourth point of caution we would like to raise concerns the ACI's applications in networks with a scaled policy score when the researcher establishes a cut-off value of more than zero, which means ties between actors who hold slightly different beliefs are included. If a coalition has a chain-shaped structure, the beliefs of an actor on one edge and those of an actor on the opposite edge can differ considerably. Imagine a case in which we tolerate a 0.25 difference in the belief score and identify a coalition in which actors are connected as A-B-C-D-E. In theory, in this case, the belief scores of actors A and E can be 0.0 (completely against a policy) and 1.0 (completely in support of the same policy). In practice, however, this limitation is relatively minor because most empirical networks exhibit a tendency for transitivity: If actors A and B are connected and actors A and C are connected, then B and C tend to be connected as well, and the problem therefore does not occur. Moreover, a formal method of solving this problem is to set an additional criterion for the existence of a coalition, such as by solely considering coalitions whose diameter (i.e., the maximum geodesic distance within a coalition) is no higher than a certain value (e.g., 3). By setting this additional criterion, the above A-B-C-D-E network would no longer count as a coalition, because its diameter would be 4, which exceeds the threshold.

Thus far, we have discussed the limitations of the ACI in relation to its mathematical properties. When applying the ACI to empirical studies, a salient further caveat is that the index does not encompass all aspects that are of interest to ACF scholars. The intentions of policy actors, the content of their communication, and the context of coalition politics are beyond what the ACI measures. Therefore, results provided by quantitative indicators such as the ACI should always be interpreted in combination with case knowledge. Moreover, qualitative studies have contributed immensely to the development of the ACF (e.g., Elliott & Schlaepfer, 2001; Dudley & Richardson, 1999) and will of course continue to be necessary alongside quantitative studies using indicators such as the ACI.

The ACF assumes that the beliefs policy actors hold lead them to coordinate action with like-minded actors. However, it is also possible that the process works the other way around: Actors' beliefs may become more similar as a result of coordination and policy learning. Indeed, the ACF argues that policy forums and cross-coalition ties can facilitate such learning. Gronow et al. (2021) demonstrated that when multiple social contacts "expose" an actor to beliefs that differ from the actor's own beliefs, this makes it likely that the actor changes their policy beliefs. When applied longitudinally, the ACI can provide insights into the co-evolvement of coordination and beliefs. For example, the ACI can test whether the existence of cross-coalition ties is conducive to policy learning across coalitions.

There are many other potential avenues for future research and theory development using the ACI. An obvious avenue is using the index for comparative work and theory development based on these comparisons. However, the ACI also makes it possible to compare the strengths of various potential drivers of coordination within a policy subsystem. This is important, to provide one example, because the precise role that policy core beliefs play in coalition formation relative to other beliefs has been debated (Kukkonen et al., 2017). To advance this debate, the ACI can be calculated separately for policy core beliefs and secondary beliefs to assess whether policy core beliefs indeed contribute to coalition formation more strongly than secondary beliefs, as hypothesized by the ACF.

Another avenue of research focuses on ACF hypotheses that have seldom been empirically tested. According to Jenkins-Smith et al. (2017, p. 148), two of five of the ACF's hypotheses concerning coalitions have not received much attention. The first states that public administration agencies tend to be more moderate in their beliefs than the interest groups that are their coalition partners, whereas the second states that so-called purposive groups exhibit a tendency to constrain their expressions of their beliefs more often than material groups (Jenkins-Smith et al., 2017, p. 149). To test these hypotheses, one requires a criterion to define what constitutes a coalition. This can be achieved by using the ACI and setting a common cut-off value for ties. After identifying coalitions, one can test whether administrative agencies' beliefs are indeed significantly more moderate than those of interest groups in each coalition, as well as whether purposive groups' beliefs are significantly more constrained than those of material groups. As this example illustrates, whatever hypotheses one posits concerning coalitions, the ACI is a reliable tool for testing them because the systematic identification of coalitions is a basic requirement for testing ideas related to advocacy coalitions. Furthermore, ACI or its constituent sub-scores can be used as dependent or independent variables in multivariate analyses. To offer two examples, it is first possible to explain the particular actor attributes (independent variable) that explain cross-coalition ties (dependent variable), while it may prove fruitful to, secondly, investigate questions such as whether the possession of a high cross-coalition ties score (independent variable) renders an actor politically influential (dependent variable).

Finally, although the index is designed to analyze advocacy coalitions, its basic concept and calculation methods can be imported into other research contexts within the field of public policy by transforming the policy belief element into any other actor attribute that is hypothesized to be a catalyst behind the formation of network ties. Many theories agree on the importance of coalitions or alliance building in policy processes, but vary in terms of what each theory identifies as the significant driver of coalition formation, such as mutual trust and reciprocal norms (Henry et al., 2011), the need for resources (van Dyke, 2003; Jenkins, 1983), or one's chosen political strategy (Zajak et al., 2018). All of these theories share the necessity to examine the drivers of coalition formation, to divide actors into coalitions, and to identify actors who are not behaving in accordance with the assumed impetus of coalition formation. The ACI can facilitate these tasks. Thus, the contribution of the ACI to the literature on advocacy coalitions can be extended to other fields of inquiry wherein data concerning network connections and actor attributes are available.

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ENDNOTES

1. Because the cross-coalition ties score tends to correlate with the homophilous ties score, it makes sense to control for the homophilous ties score (which is what the CCH ratio does) when the two are used together. While one could instead simply compare the number of cross-coalition ties and homophilous ties, this procedure would not take into account how many like-minded/dissimilar actors are "available" in the subsystem, as both constrain the realizable number of each type of ties. Hence, we believe the CCH ratio can capture the role of actors better in the policy subsystem than a simple ratio. We thank Dr. Juho Vesa for suggesting this ratio.

2. The R script for calculating ACI is provided in Appendix E.

3. The number of coalitions identified by manipulating the cut-off value is provided in Appendix C in the Supporting Information. Regarding the choice of cut-off value, if the belief score is based on a five-point Likert scale (translated into 1, 0.75, 0.50, 0.25, and 0.00), a value of less than 0.25 might be too strict because it indicates that we differentiate between those who answer "strongly support" and those who answer "support," whereas 0.50 might be too relaxed because it crosses the line from "supporting" to "opposing". If one is using a composite variable, 0.5–1.5 SD is perhaps a reasonable discrete value.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the Supporting Information section.

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