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The Hierarchy of Beliefs and Coordination: A "Chicken and Egg" Problem

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Abstract

This article revolves around the hierarchy of beliefs and coordination. The Advocacy Coalition Framework (ACF) emphasises political actors' role and their beliefs in public policymaking. As soon as actors share beliefs, they coordinate actions to affect policy outputs and outcomes decisively. Thus, according to the ACF, beliefs are a key driver of coordination, and manifold studies have tested this relationship. However, does coordination also affect beliefs, i.e., contribute to adopting similar beliefs? The literature, which comprises political and policy network studies, may argue so, referring to social influence and contagion. In this article, we combine the ACF with social and political network analysis to disentangle causality between coordination and beliefs in both directions and investigate whether a mutual relationship exists between the two concepts. To do so, we utilise the same policy subsystem with the same set of actors over several points in time and analyse how beliefs and coordination coevolve over time. We draw on data from the Swiss climate policy subsystem, spanning almost two decades. Specifically, we build a network coevolution model to assess how the political network (ties reflecting coordination) and belief network (ties reflecting belief similarity) influence each other over time. Our results do not definitively answer the "chicken and egg" question: What comes first—beliefs or coordination? Instead, they demonstrate that coordination and belief change mutually reinforce each other.

Keywords

advocacy coalition framework; belief similarity; climate policy; coordination; social influence; social network analysis; Switzerland

1. Introduction

In this article, we tackle a typical "chicken and egg" question, i.e., an issue of reverse causality that has not been sufficiently addressed yet in the respective literature (exceptions: Gronow et al., 2021; Henry et al., 2021). The Advocacy Coalition Framework (ACF; Nohrstedt et al., 2023; Sabatier, 1988) emphasises the role of political actors—such as political parties, civil society organisations, interest groups, or research and higher education institutions—and their beliefs in public policymaking. As soon as these political actors share beliefs, they coordinate actions to affect policy outputs and outcomes decisively. Thus, according to the ACF, beliefs are a key driver of coordination—i.e., alignment of actions in a policy process to advocate for one's own interests and/or policy implementation—and manifold studies have tested this relationship (e.g., Koebele, 2020; Pierce et al., 2022; Satoh et al., 2023). However, does coordination also affect belief similarity, i.e., contribute to adopting similar beliefs?

To answer this question, we combine policy process theories—and more concretely, the ACF—with social and political network analysis. We conceive of different moments in a political process as a network of actors who coordinate and who think alike. We then investigate when and how the two (belief similarity and coordination) mutually impact each other.

The ACF develops several seminal hypotheses on how political actors—such as parties, NGOs, or interest groups—organise in policy processes and within advocacy coalitions. Advocacy coalitions are groups of like-minded actors that coordinate their actions. Therefore, the three-tiered belief system of actors and coalitions plays an important role and often is defined as a driver for coordination (Henry, 2011). Within, but also outside of, the ACF, the so-called belief homophily hypothesis was tested, which clearly investigates whether similar or the same beliefs impact the creation of coordination ties (e.g., Calanni et al., 2015; Ingold & Fischer, 2014). However, these extant studies' results are mixed depending on various political systems (e.g., Gronow et al., 2019), different levels of conflict prevalent in a subsystem (e.g., Kammerer et al., 2021), and nascent subsystems (e.g., Ingold et al., 2017; Lemke et al., 2023; Wiedemann & Ingold, 2024). Thus, depending on the context, beliefs seem to be more or less decisive in driving coordination in a policy process. These diverging results incentivised us to investigate this relationship further between beliefs and coordination.

For example, the literature on social influence and contagion would argue for reverse causality or at least adopt a coevolution perspective. As soon as actors coordinate and engage in what can be classified as a strong and mutual tie, a social influence process is nudged, potentially leading to alignment of their policy beliefs. Different existing political and policy network studies have confirmed this contagion or social influence process or have emphasized the coevolution between homophily and influence (Cranmer et al., 2020; Gronow et al., 2021; Teodoro & Prell, 2023).

Knowing more about the relationship between beliefs and coordination seems important for several reasons. First, it helps us understand when and how politically involved actors build subgroups and coalitions to impact policy outputs and eventually induce policy change. Second, it potentially combines the macro-, meso-, and micro-levels of policymaking. For example, coordination is very much shaped by macro-level political institutions and venues (Ingold et al., 2025) and can be steered by formal and informal rules (McGinnis, 2011). Actors can meet and coordinate only if they know and can interact with each other, i.e., coordination needs informal and formal institutions and venues to create opportunity structures for actors to interact. This is very different when thinking about belief systems: These ideologies can differ from one political actor to another and are linked to the actor's socialisation, experiences, and problem perceptions. Beliefs shape policy processes from the inside out, as they are inherent to each actor and can be very individualised. Thus, our results reveal whether macro-and meso-elements of the political process (institutions and networks; Lubell et al., 2012) impact the micro-level of actors' beliefs, or vice versa. Furthermore, our findings also speak to how much room authorities have to manoeuvre in shaping policy processes: They might have easier access to the macro- and meso-levels to impact institutions and procedures, rather than induce changes at the micro-levels of actors' ideologies. However, this depends heavily on both the investigated jurisdiction's institutional regime and subsystem-specific characteristics (Ingold et al., 2025).

Second, the question arises of how much social influence a policy process needs. If we can confirm the hypothesis that coordination leads to alignment of beliefs and belief homophily, this means, very simply put, that actors involved in the same policy subsystems start to think more and more alike. In this scenario, it can be the case that political actors from different advocacy coalitions start to have similar understandings of certain things over the years, e.g., the policy problem or decision-making process (Frick et al., 2023; Gronow et al., 2021). From this perspective, beliefs and coordination start to become two sides of the same coin. However, the related literature so far has provided little evidence that subsystems converge over time towards a unitary subsystem with one single coalition. This may not be the aim of policymaking, i.e., to function as a purely technocratic or engineering procedure in which solutions to problems are designed and implemented. Instead, it may be a bargaining process and a negotiation among actors with different beliefs, needs, and interests.

In this article, we juxtapose insights from social network theory—and, more concretely, contagion and social influence—with insights from policy process theories by examining the same policy subsystem over time. We use survey and text data to code actors' beliefs and investigate coordination in Swiss climate policy over almost two decades. We ultimately create two distinct networks: one comprising shared beliefs (through belief similarity ties) and one in which the same set of actors shares coordination ties. Via a network coevolution model, we assess how the coordination network (ties reflecting coordination) and belief network (ties reflecting belief similarity) influence each other over time.

The article is structured as follows: After a theoretical introduction to the ACF and network theory perspective, we present the hypotheses. In the methods section, we introduce the case of Swiss climate policymaking over two decades and outline our data-gathering and analytical methods. We then present our results before discussing them, considering the hypotheses. Our results indicate that beliefs and coordination mutually influence each other over time, as we found evidence for both hypotheses: Political actors select their coordination partners based on shared beliefs, but also align their beliefs with those of actors with whom they frequently coordinate. We also found that political actors coordinate regardless of whether they share policy core beliefs (PCBs) or secondary aspects (SAs). This increased coordination makes actors more similar in terms of their PCBs. Thus, negotiating SAs over time might bring actors together, leading to alignment in their PCBs. We end the article with a general conclusion, limitations, and outreach.

2. Theory and Hypotheses

The ACF is one of the most prominent policy process theories, and as its name suggests, it is interested in the establishment and evolution of advocacy coalitions and their potential impact on policy change (Nohrstedt et al., 2023). According to the ACF, advocacy coalitions comprise beliefs and coordination, which are the two elements of interest here. Political actors in a subsystem engage in joint action, i.e., coordination based on similar beliefs (Henry, 2011; Ingold, 2011). This assumption is tested very often with what ACF scholars call the "belief homophily hypothesis" (Henry et al., 2021; Satoh et al., 2023), which asserts that two actors establish a coordination tie between each other as soon as they share beliefs and policy preferences within the subsystem of study (Ingold & Fischer, 2014). The belief homophily hypothesis has been confirmed in many subsystems and applications, but ACF scholars have concluded that the degree of conflict seems to matter (Fischer, 2014; Kammerer et al., 2021). In high-conflict subsystems, beliefs seem to be an important driver of coordination (see Ingold & Fischer, 2014), whereas in more collaborative or even community contexts, hierarchy and power are more relevant (Calanni et al., 2015; Pierce et al., 2017). In such collaborative or local subsystems, it seems that a general understanding of the problem and its potential solutions already exists, and that power devices are more decisive for tie establishment. However, in our context, we focus on the traditional ACF view on beliefs and coordination to posit the following hypothesis:

> H1: If two political actors share similar beliefs, they are more likely to establish a tie in the coordination network over time.

The ACF also makes an important distinction between different beliefs' relevance to coordination and, ultimately, coalition formation and development. To elaborate more on this, we briefly introduce the three-tiered ACF belief system. The first tier, deep core beliefs, comprises the fundamental ideologies of a political actor that are valid across various political topics and policy subsystems, reflecting "general convictions of how a society should be organised, like, for example, the level of state intervention, the handling of the challenges as imposed by globalisation or matters of social equity" (Kammerer, 2018, p. 169). The second tier, PCB, involves translation of deep core beliefs into specific policy subsystems, such as regional planning or national energy policy. PCBs include beliefs on how a concrete problem or issue on the subsystem's agenda should be approached. The final tier comprises SAs and embraces the more instrumental aspects of a policy subsystem, such as policy measures, monitoring, or finances.

According to the ACF, the likelihood of changing beliefs increases from the deep core to the policy core and, ultimately, to the SAs, i.e., deep and PCBs are more resistant to change and serve as the glue between members of an advocacy coalition—at least in theory (Gabehart et al., 2022). However, the ACF is not very clear on the causal relationship between belief levels and coordination. Political negotiations—and the coordination they require—are driven by different factors, which also depend on the venues in which actors are involved (Fischer, 2014; Ingold et al., 2025). In some situations, SAs may well drive coordination between two actors, particularly when they are part of opposing coalitions. Nevertheless, in the context of the establishment and maintenance of advocacy coalitions, we expect PCBs to make a stronger impact on tie formation in the coordination network than SAs. Therefore, we posit the following hypothesis:

> H2: If two political actors share PCBs, in contrast to SAs, they are more likely to establish a tie in the coordination network over time.

The literature on policy and political networks would not entirely disagree with the belief homophily hypothesis, but in contrast to many ACF studies that have examined a subsystem at one point in time, political network analysis often studies a network over time, thereby observing the phenomenon of social influence and contagion (Cranmer et al., 2020; León-Medina, 2023). According to this phenomenon, once two actors in a network share a tie, they start to influence, or "infect," each other on other aspects as well, such as behaviour, ideologies, or preferences (León-Medina, 2023; Tam Cho, 2003; VanderWeele, 2011). Gronow et al. (2021) applied this to the ACF and, to a certain extent, could confirm that sharing ties leads subsystem actors to change their beliefs, which is also an important component of policy-oriented learning. Actors adapt their beliefs over time in a subsystem. In this process, it might be possible that they are affected mainly by those to whom they are connected. Our interest here is not primarily in belief change or policy-oriented learning, but rather in the reverse causality of what is outlined in H1. Thus, we posit:

H3: If two political actors share a coordination tie, they are more likely to share beliefs over time.

3. Research Design: Case, Data, and Model Specification

To test our hypotheses, we measured coordination between political actors and shared beliefs at three consecutive time steps (see Figure 1). We assessed the latter through similarity in the portfolio of supported beliefs (belief similarity). Thus, we needed data on the same set of actors in the same subsystem over a long period of time. As presented in Figure 1 and explained in detail in Section 3.2, such data are available for Switzerland's climate policy subsystem around important phases in the policy process related to the CO_2 Act and later the Climate Protection Act, which together represent the heart of Switzerland's climate policy.

3.1. A Brief History of Switzerland's Climate Policy

Switzerland's climate policy history dates back to the 1980s, with air and energy policies shaped by concerns over forest dieback, the oil crises of the 1970s, and the 1986 Chernobyl disaster. These events heightened awareness of the need to enhance energy efficiency, reduce harmful emissions, and decrease reliance on fossil fuels. The 1992 UN Rio Summit, alongside then-Minister for Home Affairs Flavio Cotti's commitment to make Switzerland a global leader in combating climate change, propelled these efforts further. Cotti's push for one of the world's first domestic CO_2 taxes faced significant opposition, particularly from economic stakeholders, leading the Swiss government to adopt a broader, cross-sectoral approach, instead of relying on a single policy tool (Ingold, 2011; Kammerer et al., 2020; Lehmann& Rieder, 2002). Thus, in the mid-1990s, a first draft of the CO_2 Act was discussed, leading to implementation of the first version of the CO_2 Act, adopted in 2000 (Ingold, 2008, 2011).

The first CO_2 Act aimed to meet the Kyoto Protocol's requirements for a greenhouse gas reduction target of 8% for combustibles and 10% for motor fuels, compared with 1990 levels (Federal Office for the Environment, 2010). The plan relied on a mix of voluntary measures and a conditional CO_2 levy on motor fuels and combustibles. However, by 2002, it became clear that voluntary measures alone would not suffice, prompting the federal government to introduce the levy. Despite this, opposition from the economic and energy sectors resulted in a partial revision of the CO_2 Act, which included a levy only on combustibles and maintained weaker, voluntary measures for the traffic sector (Niederberger, 2005). Specifically, some transport lobbyists and petrol importers suggested a new instrument, the Climate Cent (Stiftung

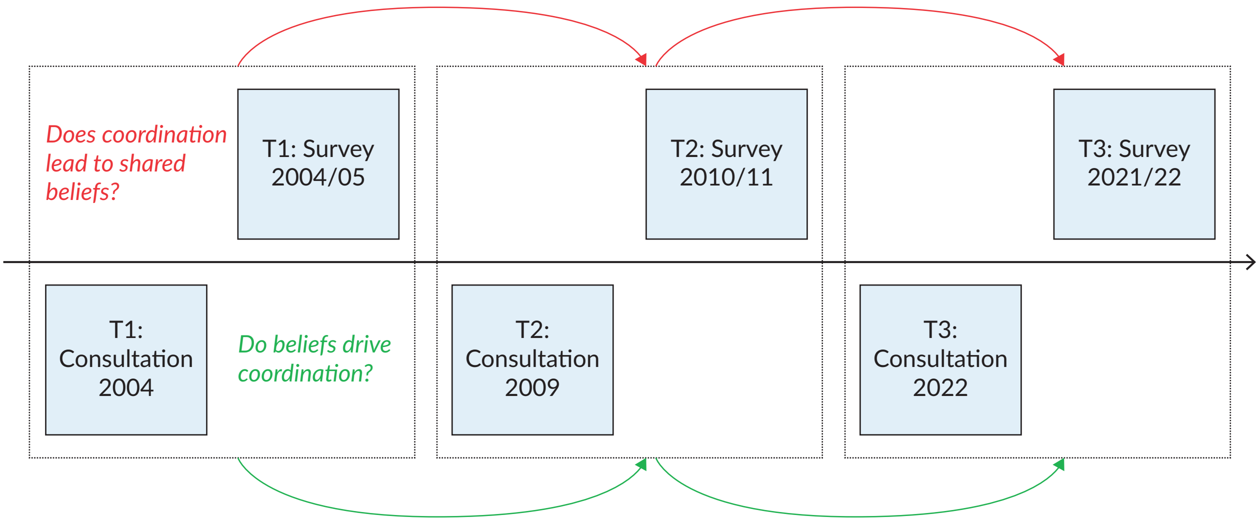


Figure 1. Overview of datasets from a chronological perspective.

Klimarappen, 2013). The partial revision was accompanied by a public consultation in 2004 (T1: Consultation data, 2004), in which stakeholders were invited to state their opinions on various instruments. The revised act entered into force in 2005 (T1: Survey conducted in winter 2004–2005; see Ingold 2008, 2011; Ingold & Fischer, 2014).

Dissatisfaction with these outcomes led to further revisions spurred by the Climate Alliance, which comprised NGOs, left-wing, and green parties. In 2008, the alliance initiated the popular initiative "For a Healthy Climate," which called for a 30% reduction in emissions by 2020 and enshrinement of this target in the Swiss Constitution. In 2009, the government's response was a new draft of the CO_2 Act, which proposed a levy on motor fuels and other measures, such as compensation obligations for oil imports and standards for passenger cars. Stakeholders assessed the draft in a public consultation in fall 2009 (T2: Consultation data, 2009). The revised CO_2 Act was passed in 2011 and entered into force in 2013. However, the new act contained what for that time was a moderately ambitious 20% reduction target by 2020 compared with 1990 levels without including a CO_2 levy on motor fuels, which powerful economic interests blocked yet again (T2: Survey conducted during 2010–2011; Ingold & Fischer, 2014).

The most recent development in Swiss climate policy came with the approval of the Climate Protection Act, a comprehensive framework outlining Switzerland's climate objectives, adopted in 2023. The act emerged after several failed attempts to revise the CO_2 Act in line with Switzerland's commitments under the Paris Agreement, which included a 50% reduction target by 2030. The first draft of a revised CO_2 Act was in public consultation in 2016 but failed in 2017 in parliament after both the left, green parties, and right-wing parties rejected it, as the proposal was viewed as either too lenient or too stringent. However, growing public pressure, particularly from the Fridays for Future movement, led to the introduction of a more ambitious proposal in 2019. This proposal, which included measures such as a flight ticket levy and a new climate fund, passed in parliament in 2020, driven in part by what is known as the "Greta effect" (The Federal Assembly—The Swiss Parliament, 2019), which fostered policy learning and a shift in coalition dynamics within the climate policy arena. Despite this, Swiss citizens rejected a referendum led by the Swiss People's Party and various industry groups in a popular vote in June 2021 (T3: Survey conducted in 2021–2022; see Braissant, 2023). Following this setback, the Swiss government adopted a new approach based on funding incentives instead of new levies or other regulatory measures. After a promising public consultation, this new approach led to the successful passage of the Climate Protection Act in June 2023 (T3: Consultation data, 2022).

3.2. Measuring Coordination and Belief Similarity

To measure *coordination*, we drew on existing surveys of Switzerland's climate policy elite conducted in 2004–2005 (T1), 2010–2011 (T2), and 2022 (T3; see Braissant, 2023; Ingold, 2008, 2011; Ingold & Fischer, 2014, for a detailed description of the data collection procedure for each survey). Most importantly for this study, the elite surveys comprised questions about the respondents' collaboration networks. Very specifically, the respondents were asked about their direct and close collaboration partners in the Swiss climate policy subsystem at a given time, as they relate to a specific process, disregarding shared beliefs. We identified the key political actors from government, political parties, business, civil society, and science, and asked them questions about their collaboration partners and reputational political actors. For all four surveys, actors were identified following a standard procedure for elite and policy network studies (Knoke et al., 1996)—a combination of the decisional, positional, and reputational power approaches.

We used this question about collaboration as a proxy to generate the three *coordination networks*, as the survey questions aimed to unveil alignment of actions within a subsystem independent of belief similarity. This aligns with a common distinction between coordination, i.e., alignment of actions vs. collaboration (i.e., alignment of objectives; Castañer & Oliveira, 2020). In doing so, we also followed good practices used in many other political network analyses and ACF applications (Ingold, 2011; Koebele, 2019). We constructed three binary, undirected (symmetric) matrices with the value (1) when two actors in the survey indicated that they collaborated, i.e., coordinated their actions, and with the value (0) if they did not indicate collaboration. Notably, we symmetrised ties, i.e., reciprocated collaboration, as soon as a political actor mentioned a collaborative relationship.

To measure *belief similarity*, we compiled a novel dataset based on information retrieved from actors' positions outlined in public consultation procedures linked to specific climate policy processes (see the case description in Section 3.1). In Switzerland, an institutionalised consultation procedure (*Vernehmlassungsverfahren*) includes various governmental (encompassing political parties in parliament and government) and nongovernmental actors in the decision-making process at an early stage (Linder, 2010). In such consultation procedures, political actors are aware that high-level officials (and potentially other stakeholders) will read their policy preferences and positions. As a result, they may frame these positions more strategically—sometimes more assertively or with stronger language—to signal and advocate for their interests. In contrast, when surveyed for research purposes, they may provide responses that align more closely with what is expected socially or that reflect a more moderated stance (Ingold et al., 2020).

We coded text-as-data from these consultations and constructed actors' beliefs at three distinct time points: 2004 (T1), fall 2009 (T2), and 2022 (T3). The raw dataset is displayed in three two-mode matrices, with actors in rows and different beliefs in columns. The datasets distinguish between PCBs and SAs but do not include deep core beliefs. Most often, actors outline their preferences for SAs and sometimes emphasise these choices with justifications that can be classified as PCBs (Markard et al., 2016). However, it is very difficult to retrieve deep core beliefs from these texts.

The data were collected based on a pre-defined coding framework that measures an actor's agreement with a policy core belief or secondary aspect on an ordinal scale from 1 to 4, in which 1 indicates *strong agreement* and 4 indicates *strong disagreement* (Rufer, 2024). We collected data on the same set of seven PCBs (see Table 1; PCBs column) for all time steps. In contrast, we allowed the SAs to vary over time and cover key developments in the Swiss climate policy process most accurately (see Table 1; SAs column). Based on these three two-mode matrices, we calculated belief similarity for all actors and for each period using Gower's distance (Similarity = 1—Gower's distance), which is well-suited for ordinal datasets (Gower, 1971; Podani, 1999). This resulted in three one-mode similarity matrices per phase.

We then dichotomised the three similarity matrices to values of 1 (reflecting *high agreement* similarity) and 0 (when no high belief agreement was reached between two actors). We dichotomised the matrices using a period-specific threshold set at the 75th percentile (upper quartile) of each period's similarity distribution. This approach ensures that only the most similar pairs (relative to the distribution in each period) are retained for further analysis. By adapting the threshold dynamically per period, we avoided imposing an arbitrary absolute cutoff and preserved comparability over time. Thus, the *belief network* dataset comprised three binary one-mode matrices.

This dichotomisation was necessary because the selected coevolution model does not allow for weighted networks as dependent variables. This strategy has limitations, as dichotomisation induces a loss of detailed

Table 1. Overview of actors and beliefs per time step for model specification.

Time step	Period	Belief network	Coordination network	SAs covered during the respective period	PCBs
T1	2004–2005	Consultation 2004 Actors: 24 PCBs: 7 SAs: 5	Survey: 2004–2005 Actors: 29	CO2 levy on combustibles CO2 levy fuels Partial earmarking of the CO2 levy EU ETS Climate Cent	Ecological efficiency Redistributional equity Market competitivity Seriousness of the problem Switzerland's international role State intervention Target group flexibility
T2	2009–2011	Consultation 2009 (fall) Actors: 35 PCBs: 7 SAs: 4	Survey: 2010–2011 Actors: 47	CO2 levy on combustibles CO2 levy fuels Climate Cent Voluntary measures	
T3	2022	Consultation 2022 Actors: 34 PCBs: 7 SAs: 8	Survey: 2022 Actors: 36	Reduction target (50%) EU ETS CO2 levy on combustibles Increase CO2 levy Exemption from the CO2 levy Compensation obligation for fuel imports Exemption from the ban on fossil-based heating systems Education and training	

information regarding the alignment of individual beliefs over time. To overcome this issue, we ran robustness checks based on the two-mode matrices (see Appendix B, Table 2 in the Supplementary File).

The political actors covered by the three survey datasets set the boundaries for the selection of actors in this study. Thus, in the first step, we compiled a list of all actors surveyed in all free time steps and then removed these governmental actors (i.e., administrative agencies, bureaucrats) that were not involved in public consultations (they are the convenors of it, but do not express their beliefs and policy positions). We ran a sensitivity analysis, i.e., a simple stochastic actor-oriented model (SAOM) based on the same time steps, but without cross-network effects, including governmental actors, to ensure that exclusion of governmental actors did not bias our results. The models yield comparable results for our structural terms and covariates (see Online Appendix B, Table 1 in the Supplementary File). We then coded three consecutive public consultations for each political actor in which data were available, i.e., those who participated in the respective consultation.

3.3. Model and Model Specification

SAOMs are designed to assess tie formation dynamics in panel network data, i.e., each network is measured at discrete time steps. We applied an extension of SAOMs to investigate the coevolution of coordination and shared beliefs, i.e., belief similarity. Thus, to test our hypotheses, we combined the survey and consultation datasets along three time steps. As SAOMs model change in the network and behavioural data, via mini steps, it is crucial that both are in immediate, timely relation (Ripley et al., 2025). In our case, in each time step, the survey and consultation data belonged to the same policy process related to the CO_2 Act (see case description in Section 3.1 and Figure 1), and the survey data collection and consultation in all three periods were also conducted around the same time.

To test our hypotheses, we employed a coevolution model to capture the joint dynamics between two one-mode networks—collaboration and belief similarity. This setup adapted the multiplex SAOM framework introduced by Snijders et al. (2013), extending it from the more frequently used one-mode/two-mode configuration or behaviour data in the form of individual actor attributes (e.g., Brouwer & de Matos Fernandes, 2023; Teodoro & Prell, 2023) to two interdependent one-mode networks observed in the same actor set (e.g., Wang & Dong, 2025). This setup seemed to be the best model strategy, given our specific data structure and hypotheses, which focused on belief similarity, rather than a specific directed political orientation or preference, e.g., pro-climate or contra-climate. We ran a robustness check using the one-mode/two-mode approach, but only using the PCBs and SAs present across the three time steps. The models yield comparable results (see Appendix B, Table 2 in the Supplementary File). Thus, this setup offered a conceptually consistent and technically supported extension of existing multiplex models (Ripley et al., 2025). Moreover, belief similarity functions analogously to an actor attribute, so our specification parallels classic network behaviour coevolution logic (see Steglich et al., 2010) while modelling the mutual influence between collaboration and belief similarity.

To run the selected coevolution model, all network matrices must have the same dimensions across all time points, i.e., the same number of actors in each matrix. However, in practice, some actors were present only during certain survey periods and not in others. To address this, we added what are called structural zeroes, i.e., placeholders indicating that an actor or belief was not present at a specific time. These are not actual zeroes representing the absence of a tie, but rather fixed positions in the matrix that reflect the unavailability of an actor or belief during a given time step.

We began by compiling the full list of all actors (n = 79) who appeared across the three survey periods. For each period, if a specific actor was not surveyed, we added them to the matrix with structural zeroes, ensuring consistency in the representation of actors. By doing this, we ensured that all matrices have consistent dimensions—making it possible for the model to trace how ties form or disappear over time, even if some actors or beliefs were temporarily absent.

3.3.1. Short Introduction to SAOMs

SAOMs assume that unobserved changes in the network (at the tie level) arise between measurement points. These changes in ties occur because actors in a network strive to optimise their social environment (actor-based). To model network evolution, SAOMs estimate an evolution function (also an objective function):

$$f_i\ (\beta, x) = \sum_k \beta_k s_{ki}(x) \qquad \text{(Eq. 1)}$$

The objective function models the probability of a tie change in the network, given that an actor can make a change, i.e., it reflects the "rules for network behaviour" (Snijders et al., 2010, p. 47). These rules of behaviour are determined by the state of the network, i.e., the ties and nodes present at a specific point in time, as well as covariates (i.e., actor characteristics). The function $f_i\ (\beta, x)$ reflects the value of the objective function for actor i depending on the state of the network x. The right-hand side of the equation comprises, as in generalised linear regression models, a linear combination of effects, i.e., statistical parameters that reflect network (sub)-structures, such as the tendency to reciprocate ties or triangulate or form ties with similar alters. Specifically, x represents the observed network structure, and β_k is the vector of parameters estimating the magnitude and direction of various structural effects, cross-network effects, or covariates on actor *i's* ties (in this case, coordination ties and belief similarity). $s_{ki}(x)$ reflects the value of the k-th network statistics (e.g., density, transitivity, homophily, etc.) for actor i calculated from the current network.

For example, if an actor prefers to form ties with "friends of friends," there will be a positive and significant transitivity parameter in the objective function. The parameter estimates are gathered by simulation. Specifically, using a current estimate, the model simulates a chain of tie changes, resulting in a new graph per simulation round. The new graphs are then compared with the observed network data. Next, the parameter estimate is tuned based on any discrepancy until all parameter estimates converge. Note that SAOMs condition the estimation on the first observation point. Thus, they model the process of change and not the network structure at a particular point in time.

For this analysis, we used a variation of SAOMs to model the coevolution of the one-mode coordination and the two-mode networks that measure shared beliefs. Thus, we modelled multiplex dynamics (Snijders et al., 2013) based on the state of each network, the respective actor attributes, and multiplexity effects.

Our model's main goal was to disentangle how shared beliefs cause coordination over time and to test for reverse causality. Furthermore, we also distinguished between different types of beliefs, i.e., we tested whether, as predicted by the ACF, PCBs drive the formation of ties in the coordination network more strongly than SAs, such as preferences on policy instruments and technicalities.

3.4. Model Specification

In this section, we present the model's specifications. We start by introducing dyadic and nodal within-network effects (uniplex network model specification), describe the coevolution effects we included (multiplex network model specification), and end by presenting our control variables. We estimated our models using the RSiena package available for the programming language R (Ripley et al., 2025; Snijders, 2017). See Table 2 for the full model specification.

3.3.2.1. Rate Constants

The most basic terms in the models are *rate constants* (coordination rate, belief similarity rate; see Table 2). These terms indicate the rate of change from one period to the next. As described in Section 3.2, we included three distinct coordination and belief similarity networks (see Table 1). Thus, our models (see Tables 3 and 4) include two rate constants for each network type, in which the first period is used as a baseline. Positive and significant rate parameters mean that a change is happening from one period to the next.

3.3.2.2. Dependency Terms (Uniplex)

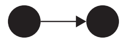
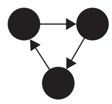
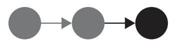
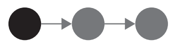
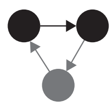
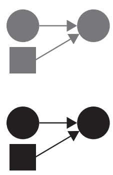
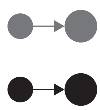
Our models contained several basic uniplex network dependency terms, which control for structural effects of existing patterns or belief similarity (see Table 2). The most basic is the *density* term of an actor i. This term must be included in all models. It reflects an actor's tendency to have ties in the coordination networks at all or demonstrate high belief agreement, i.e., have ties in belief similarity networks. As such, it captures tie formations not explained by other configurations, i.e., random or unexplained ties, and can be interpreted like an intercept in a given network model. As most social networks are sparse (i.e., they have a density below 0.5), network models often generate a negative parameter estimate for the density/outdegree effect (Snijders et al., 2010).

Another common feature of most social networks is transitivity, network closure or clustering, i.e., the tendency of "friends of friends to become friends" or build new ties in an actor's immediate neighbourhood (Snijders et al., 2010, p. 47). In our case, the respective terms measure political actors' tendency to coordinate their actions in the climate policy subsystem with actors who are already close to them via already-established partnerships in the coordination network. Specifically, we included one term to cover clustering in the coordination network. *Transitive ties, coordination*, models triadic closure in networks, i.e., actors' tendency to form transitive ties in coordination networks: If actor A coordinates with B, and B coordinates with C, then A is more likely to coordinate with C. As transitivity or network closure is common for social networks, we expect large, positive parameter estimates.

We opted for a simple clustering term, and only in the coordination network, to avoid model overfitting and multicollinearity. Particularly in coevolution models, cross-network effects tend to be correlated with clustering network statistics. Thus, including complex structural terms alongside cross-network decencies can make it difficult to disentangle their individual contributions and inflate standard errors (Ripley et al., 2025).

For a detailed description of network dependency terms, please consult the SIENA Manual (Ripley et al., 2025).

Table 2. Model specification.

Name	Description	RSiena term	Research Design	Time steps	Illustration
Coordination rate	Indicates the rate (speed) of change in the coordination network from one period to the next. Or put differently, the rate at which actors can change their coordination behaviour	Rate	Constant	T1-T2 T2-T3	
Belief similarity rate	Indicates the rate at which actors update their belief similarity from one period to the next	Rate	Constant	T1-T2 T2-T3	
Density, coordination	Tendency to form coordination ties	density	Endogenous effect coordination network	Average across periods	
Density, belief similarity	Tendency of belief similarity	density	Endogenous effect coordination network	Average across periods	
Transitive ties, coordination	Tendency to form transitive coordination ties, i.e., a simple measure for network clustering	transTies	Endogenous effect coordination network	Average across periods	
Belief similarity direct entrainment (cross-product)	The tendency to coordinate is more likely if actors exhibit belief similarity.	cprod	Cross-network effect, H1, H2	Average across periods	
Coordination direct entrainment (cross-product)	Tendency of actors that coordinate to share beliefs is more likely (PCBs and/or SAs).	cprod	Cross-network effect, H3	Average across periods	
Coordination, indirect (transitive ties)	The tendency of actors to share beliefs (PCBs or SAs) when they coordinate with alters that share beliefs themselves.	to	Cross-network effect, H3	Average across periods	
Same actor type	Tendency to coordinate or reveal higher belief similarity with actors of the same type. Included for both networks.	X	Dyadic control	Constant	
Perceived influence (reputational power measure)	Tendency to coordinate or reveal higher belief similarity with influential actors.	X	Dyadic control	T1, T2, T3	

Notes: See Ripley et al. (2025) for detailed descriptions and formulas of the RSiena effects, pp. 129ff; grey nodes represent the belief similarity network; black nodes represent the coordination network; arrows indicate change over time.

3.3.2.3. Coevolution Terms (Multiplex)

To test H1 and H3 on the effect of belief similarity on coordination (H1) and its reverse causality (H3), we included three different terms that model between-network interdependency, i.e., cross-network effects. The first model term, *belief similarity direct* (cross-product), tested H1. The second term, *coordination direct* (cross-product), and the third term, *coordination indirect* (transitive ties), tested H3 (see Table 2). We chose these three terms because we assumed that belief similarity directly affects coordination (social selection), while belief convergence occurs over time directly and indirectly via embeddedness in sustained coordination activities (social influence). Of course, there also might be indirect effects between belief similarity and coordination. However, to avoid overspecification of the model and because these effects are correlated with other structural effects, we only included higher-order effects (transitive ties) for the belief similarity network. A significant, positive model, *belief similarity direct* parameter, indicates a positive correlation between belief similarity and would support H1. Respectively, positive and significant parameter estimates related to direct and indirect coordination would support H3.

To test H2, we ran the same model setup, but in two variations. The first tested only PCBs and the second only SAs (see Table 1). Thus, we ran different models: one using a one-mode matrix that reflects PCBs' belief similarity and the other using only SAs. For H2 to be confirmed, we should see the formative effects of beliefs on coordination only for PCBs, but not for SAs.

3.3.2.4. Covariates

We included two dyadic covariates as control variables in our model. First, we tested whether the same actor types (business, civil society, energy, science, and political party) tend to coordinate more frequently or share more likely beliefs. This variable is operationalised as a dyadic variable—i.e., a dyadic one-mode matrix—indicating whether two actors are from the same actor type (1) or not (0).

Second, we also controlled for the effect of *perceived influence* on coordination and belief similarity. In particular, extant studies on subsystems with lower levels of conflict have found evidence that actors coordinate with those whom they perceive as influential, as this increases their likelihood of influencing the policymaking process (Ingold & Leifeld, 2014; Kammerer et al., 2021). To measure perceived influence, we used a different question from the surveys introduced above. Specifically, the surveys included a question that asked respondents to identify whom they viewed as influential. To answer this question, they were presented with the same list of actors for identifying coordination partners. The data are displayed as one-mode matrices.

For this analysis, we used data from the surveys in T1 (2000), T2 (2002–2005), and T3 (2010–2012) to model past perceived influence's effect on coordination behaviour during the next period.

4. Results

In this section, we present the results from our analysis. We start with a short description of our networks and then present three different model setups in Tables 4 and 5. We build and present our models step-by-step. All models converged well, with an overall maximum convergence ratio below the 0.25 threshold (Ripley et al., 2025), revealing robust results across the different models, which are well-specified (see goodness of fit [GOF] plots in Appendix C in the Supplementary File).

Table 3. Descriptive statistics.

Network	Wave	Number of ties	Density	Jaccard similarity
Coordination	T1,	121	0.298	
Coordination	T2, Jaccard (T1→T2)	115	0.098	0.102
Coordination	T3, Jaccard (T2→T3)	68	0.108	0.364
Belief similarity (binarised)	T1	76	0.262	
Belief similarity (binarised)	T2, Jaccard (T1→T2)	182	0.250	0.274
Belief similarity (binarised)	T3, Jaccard (T2→T3)	294	0.264	0.372

Table 3 summarises descriptive statistics for the three coordination and belief similarity networks. The coordination network is relatively sparse, with densities ranging from 0.098 (T2) to 0.298 (T1). The number of coordination ties decreased from T1 to T3. Jaccard similarity coefficients indicated uneven stability across periods, with low stability between T1 and T2 (0.102) and moderate stability between T2 and T3 (0.364), suggesting substantial reconfiguration of coordination between T1 and T2. The belief similarity network exhibits consistently low densities (0.250–0.264), with a gradual increase in tie counts from T1 (76 ties) to T3 (264 ties). Stability was moderate across all periods, with Jaccard coefficients ranging from 0.274 to 0.372, indicating that around one-third to two-fifths of similarity ties are retained between consecutive waves. This suggests that while belief alignment is stabler than coordination during some intervals, it also undergoes notable change over time. This implies that coordination ties are more volatile and prone to short-term restructuring, whereas belief similarity, though still changing, is stable over time. This relative stability in beliefs could mean that shifts in coordination are not always accompanied by equally rapid changes in underlying beliefs.

The results in Table 4 relate to H1 and H3, and, as presented, we set up the model step-by-step to carefully encounter model behaviour. The *basic model* contains only the *density* term for both networks, as well as rate constants. As expected for social networks, both *density* terms are negative, and in most model variations, also significant, implying that the networks are rather sparse. The four rate constants are all positive and significant, indicating a tendency to coordinate more and align beliefs over time.

The *covariates model* indicates a positive, but not significant, association between *perceived influence* and coordination. For the belief similarity network, we identified a small negative parameter estimate. Thus, our results delivered no evidence that actors are more likely to coordinate with influential alters (see also García Mancilla & Bodin, 2020; Kammerer et al., 2021; Matti & Sandström, 2011, which arrived at similar conclusions). Furthermore, the *covariate model* indicated that political actors are not necessarily more likely to coordinate with actors of the *same actor type* (the effect is positive, but not significant), while actors of the same type are significantly more likely to share beliefs. This is an important additional finding that clearly underscores the importance of investigating actors' diverse belief systems in policymaking. Thus, actor type alone is not a good proxy for investigating belief homophily among actors involved in one policy subsystem: A comprehensive investigation of a whole portfolio of beliefs is needed, and ultimately, this is an empirical question.

Table 4. Results from RSiena estimations; standard errors in parentheses (H1 and H3).

	Basic model	Controls	Structural	Coevolution	Final
Coordination rate, T1–T2	11.099*** (3.210)	15.073° (8.484)	27.484 (34.539)	27.911 NA	17.241 (11.480)
Coordination rate, T2–T3	4.654*** (1.278)	5.224*** (1.422)	7.100* (2.817)	8.212** (3.122)	8.490* (3.389)
Density	−1.137*** (0.102)	2.139 (1.903)	−1.619 (3.071)	0.169 (1.782)	−0.787 (2.182)
Transitive ties			2.540 (2.078)	1.425* (0.714)	1.454* (0.649)
Same actor type		0.415* (0.199)	0.355° (0.189)	0.310 (0.215)	0.318 (0.214)
Perceived influence		−0.026° (0.015)	−0.026 (0.016)	−0.006 (0.018)	−0.001 (0.016)
Belief similarity, direct (H1)				1.165** (0.441)	1.131** (0.374)
Belief similarity rate, T1–T2	7.034*** (1.512)	7.101*** (1.532)	7.090*** (1.512)	8.191*** (2.070)	8.110*** (2.053)
Belief similarity rate, T2–T3	7.256*** (1.051)	7.399*** (1.057)	7.414*** (1.067)	8.643*** (1.547)	9.077*** (1.582)
Density	−0.525*** (0.066)	−0.651*** (0.095)	−0.650*** (0.098)	−0.840*** (0.107)	−0.837*** (0.106)
Same actor type		0.398* (0.161)	0.392* (0.167)	0.351* (0.171)	0.307* (0.156)
Perceived influence		0.459° (0.266)	0.257 (0.283)	0.404° (0.243)	0.277 (0.280)
Coordination, direct (H3)				−0.470 (0.656)	
Coordination, indirect (H3)				0.280** (0.089)	0.235*** (0.067)
Convergence ratio	0.0679	0.0426	0.0721	0.0849	0.0798
Iterations	10,606	10,962	10,955	11,581	11,019

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ° $p < 0.1$.

The *structural model* now adds the *transitive ties* effect. As outlined in Section 3.3.2.3 these terms often interact with cross-network effects, which is why we first investigated them in isolation and only then added coevolution terms in the *coevolution model*. We found that the combination of the selected terms captured network clustering within the coordination networks and across the coordination networks and belief similarity networks well (see also the GOF statistics in Appendix C in the Supplementary File). Furthermore, the results reveal positive and significant coevolution effects for both networks (*coordination indirect* and *belief similarity direct*), but a negative and non-significant parameter estimate for *coordination indirect*. These results support H1 and H3: First, as H1 predicted, belief similarity reinforces coordination over time. Second, increased coordination reinforces this effect by inducing further belief alignment over time, though only indirectly via coordination partners that already share beliefs. This finding indicates cross-network clustering effects at the place.

The *final model* includes all effects except the *coordination direct*, which is negative and insignificant in the previous model, and causes model degeneracy issues. The final model setup reaffirms findings from the above models and indicates that the results are robust across the different model setups. Overall, the results in our *final model* confirm H1 and H3. Beliefs and coordination appear to reinforce each other mutually, as evidenced by both directions of causality.

The results presented in Table 5 reveal the same SAOMs, but this time using PCBs and SAs separately.

The *PCB models (basic, coevolution, final)* and *SA models (basic, coevolution, final)* overall indicated the same patterns as the final model from Table 4, i.e., the model including all types of beliefs. Thus, our results do not support H2. Coordination is not driven primarily by shared PCBs. Both the PCB and SA models provide evidence of belief similarity driving coordination and the reinforcing effect of coordination on belief similarity over time. Thus, one might conclude that coordination in the Swiss climate policy subsystem is not only driven by ideology, but is also pragmatic or issue-specific when actors temporarily align based on SAs. This interpretation is reinforced by the finding that political actors of the same type seem to share PCBs more often, but they do not necessarily share SAs, allowing for coordination around technical issues or implementation concerns.

Table 5. Results from RSiena estimations, standard errors in parentheses (H2).

	Basic model PCB	Coevolution PCB	Final PCB	Basic model SA	Coevolution SA	Final SA
Coordination rate, T1–T2	11.181*** (3.195)	16.123 (12.303)	16.812 (16.690)	11.087*** (3.164)	15.645 (11.479)	16.546 (10.889)
Coordination rate, T2–T3	4.662*** (1.263)	8.292** (3.013)	8.546* (3.766)	4.636*** (1.252)	6.833** (2.356)	7.028** (2.676)
Density	−1.135*** (0.101)	−0.783 (2.315)	−0.849 (2.403)	−1.140*** (0.106)	−0.353 (2.568)	−0.221 (2.306)
Transitive ties		1.451* (0.680)	1.480° (0.804)		1.306* (0.562)	1.334* (0.578)
Same actor type		0.315 (0.226)	0.320 (0.210)		0.365 (0.226)	0.360° (0.216)
Perceived influence		0.282 (0.304)	0.269 (0.303)		0.330 (0.338)	0.344 (0.300)
Belief similarity, direct (H1)		1.144** (0.423)	1.176* (0.463)		1.416*** (0.374)	1.380*** (0.365)
Belief similarity rate, T1–T2	7.034*** (1.542)	8.036*** (2.013)	8.108*** (2.227)	4.537*** (0.850)	4.947*** (1.041)	4.951*** (1.042)
Belief similarity rate, T2–T3	7.244*** (1.026)	8.680*** (1.582)	9.111*** (1.654)	6.283*** (0.923)	7.207*** (1.278)	7.247*** (1.335)

Table 5. (Cont.) Results from RSiena estimations, standard errors in parentheses (H2).

	Basic model PCB	Coevolution PCB	Final PCB	Basic model SA	Coevolution SA	Final SA
Density	−0.526*** (0.065)	−0.844*** (0.111)	−0.837*** (0.108)	−0.789*** (0.081)	−0.959*** (0.142)	−0.942*** (0.133)
Same actor type		0.351* (0.170)	0.309° (0.162)		0.045 (0.193)	0.015 (0.188)
Perceived influence		−0.007 (0.018)	−0.000 (0.016)		0.014 (0.020)	0.018 (0.018)
Coordination, direct (H3)		−0.443 (0.560)			−0.305 (0.556)	
Coordination, indirect (H3)		0.278** (0.090)	0.237*** (0.068)		0.284° (0.147)	0.237* (0.110)
Convergence ratio	0.0550	0.0784	0.1094	0.0498	0.1110	0.1023
Iterations	10,996	11,109	10,931	10,929	10,937	11,023

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; * $p < 0.1$.

5. Discussion and Conclusion

In this article, we tackled a typical question of reverse causality, i.e., a “chicken and egg” problem. As outlined in the theory part, ACF scholars would argue that beliefs are the “glue” that binds coalitions together (Weible et al., 2020). Thus, shared beliefs, primarily PCBs, are drivers for coordination in subsystems, particularly in conflictive contexts (Koebele et al., 2020; Weible & Ingold, 2018). Thus, in this article, we tested this traditional “belief homophily hypothesis”—namely, that shared beliefs increase the likelihood of coordination (H1). However, scholars of political or social networks would argue that social selection causality also can be reversed: In the process of social influence or contagion, actors adapt their behaviour towards those alters with whom they interact most often (Cranmer et al., 2020). Thus, based on this logic, political actors who frequently coordinate with one another are expected to align their beliefs over time (H3), such as by learning from each other.

Our results contribute to this debate by disentangling social selection from social influence effects in the Swiss climate policy subsystem. Rather than supporting one hypothesis over the other, the findings support both: Coordination and belief similarity reinforce each other over time.

First, we found strong support for H1, demonstrating that actors who share beliefs are more likely to coordinate in advancing their policy interests. Our models suggest that coordination is shaped more by belief similarity—particularly in SAs than by structural or organisational factors, such as actor type or existing network patterns. Actors cluster with others who hold similar beliefs, indicating that coordination tends to follow ideological, rather than purely strategic or institutional lines. This is an interesting result, mainly for the case investigated here. For the study of belief homophily in particular, and drivers of collaboration in general, we viewed Switzerland as an extreme and atypical case—a consensus democracy in which diverse actors, including opponents, accept compromise. This generally leads to actors overcoming ideological or institutional barriers, with a high tendency to collaborate over the whole subsystem. The confirmation of H1 and the belief in the homophily tendency in our case indicates a really strong indicator of the strength of ideologies in shaping collaboration. However, future research should nevertheless explore further when coordination is driven primarily by pragmatic or situational considerations and when it reflects deeper, long-term ideological alignment. A comparative analysis that factors in diverse degrees of democracy and different political regimes would be very suitable for such an endeavour.

Second, policy processes take time and often also involve the need to coordinate with actors from "the other side," breaking away from what is known as "angel shift" and "devil shift" (Fullerton et al., 2025; Gronow et al., 2023; Leach & Sabatier, 2005; Vogeler & Bandelow, 2018). Thus, proponents of the social influence causality assumption would argue that coordination, as a form of social interaction, induces mutual learning and behavioural adjustments, eventually eliciting compromises in political negotiations, i.e., alignment of beliefs. Our results also support this aspect, and we can confirm H3: Coordination can drive belief similarity over time.

Finally, our results contribute to ACF scholarship by separating PCBs from SAs when investigating beliefs' impact on coordination. While PCBs initially foster coordination, agreement on SAs sustains and deepens coordination over time. In a policy process that typically lasts several years, negotiating and aligning on these SAs may help bring actors closer together and eventually also facilitate convergence in their PCBs, or at least a compromise finding. Thus, we cannot confirm H2, which prioritises PCBs over SAs in tie creation. Previous ACF applications have yielded inconsistent results regarding the level of beliefs that hold coalitions together (Gabehart, 2024; Matti & Sandström, 2011; Nohrstedt et al., 2023). Our analysis effectively advances this understanding through longitudinal design and triangulation among PCBs, SAs, and coordination. Our study also confirms that cross-coalition coordination is a political reality, mainly in consensus democracies such as Switzerland (Fischer, 2014, in which coordination and belief alignment are more likely at the level of SAs than PCBs. Notably, we did not include deep core beliefs in the presented analysis.

The key strength of this analysis is the availability of a dataset that covers coordination ties and beliefs over a long period, i.e., 2000–2022. While earlier attempts have been made to conduct time-dynamic analyses of the drivers of coordination, these studies have not been able to disentangle social selection from social influence in the way our study does. For example, Ingold and Fischer (2014) took beliefs and coordination data from three consecutive surveys on Swiss climate policy (the same ones that our study uses) to draw inferences about drivers of coordination (social selection). Gronow et al. (2021) pursued the opposite purpose, testing social influence through coordination and beliefs across consecutive surveys in several countries. However, with both research designs, it is impossible to disentangle the effects of shared beliefs on coordination and vice versa. In contrast, the research design of this analysis builds on investigating coordination networks and shared beliefs from different data sources and at different time steps. This reduces endogeneity issues (as beliefs stem from different datasets) and missing values (as we were able to adjust the coding of beliefs to the surveyed respondents).

However, this study also has some limitations. The first one is connected to the consultation dataset. While we tried to the best of our abilities to collect data for all surveyed actors, we could not find data for all actors in the coordination networks. On one hand, this is because not all actors always submit a statement during public consultations (after all, this is voluntary) or are not allowed to (i.e., administrative agencies and bureaucrats). On the other hand, archival records for the earlier phases were not always complete, i.e., some records were lost over time, and we had to rely on far less comprehensive summary reports. Consequently, our dataset also contains several missing values, particularly during the earlier phases. Similarly, the coordination network contains missing values, as it was not always possible to survey the same political actors, as they sometimes—not seldom, due to political reasons—refrained from responding to such surveys (Braissant, 2023; Ingold, 2008, 2011; Ingold & Fischer, 2014). Finally, in this analysis, we did not systematically disentangle the different phases based on their degree of conflict, although earlier studies of Swiss climate policy have demonstrated that the various phases differ in this regard and that in particular, phases that are more about implementing a policy are less conflictive than phases in which a new policy must be negotiated (Ingold & Fischer, 2014; Kammerer et al., 2020, 2021).

Furthermore, this is a typical and so-called elite study encompassing public and private organisations conceived as collective actors. However, important changes in policy processes over time, whether they concern the level of beliefs (and belief similarity) or coordination, stem from how important people change within organisations. In future research, the authors' case knowledge could be utilised to account for the individual level of actor beliefs and behaviour. Similarly, more reflection can be put into the conceptualisation of beliefs as ties. Following Zafonte and Sabatier (1998), the relation between two actors who support each other's position can be conceived as a weak tie. In network terms, we would argue that there must be at least the opportunity to (directly) interact with each other or know from each other's position (before expressing their own) for a belief similarity tie to be conceived as a form of coordination. Thus, future research could further investigate in what situations and venues belief similarity is a proxy for coordination, thereby rendering the investigation of beliefs and coordination a study of a so-called multiplex network.

Our results pose further implications for future research: We demonstrated how survey research and document analysis could be combined systematically to create a timeline. It is not easy, but feasible, to combine different data sources over time or between different contexts if done with care and in a systematised manner. Depending on the media landscape or ownership, experts' accessibility, interview partners, or documents, this study incentivises researchers to engage in comparative multi-method designs, be it across jurisdictions, policy issues, or over time.

In conclusion, the straightforward result of this research is that coordination and belief similarity mutually reinforce each other over time. This result is relevant to many aspects of the ACF, including coalition formation and maintenance, as well as cross-coalition dynamics within subsystems. However, it can extend beyond that and inform various policy process theories or macro-institutional approaches that examine how actors involved in policymaking interact with one another over time. Furthermore, future research could consider more variables and focus on institutions, venues, and other contextual factors.

As mentioned in the introduction, coordination might be more vulnerable to changes in the political context or institutions (e.g., participatory platforms), or it can be more easily shaped by higher-level outputs or authority decisions. Beliefs, mainly at the (deep or policy) core level, are more difficult to influence strategically outside of an actor. Thus, our results also pose concrete policy implications: During periods when coordination seems key in the policy process and ties are established, the (purposeful) creation of new (open, participatory, inclusive) venues can trigger enhanced coordination. Through these exchanges, and in the longer run, the chances of belief change, coherence, and ultimately, policy-oriented learning are higher.

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Conflict of Interests

There are no conflicts of interest to disclose.

Data Availability

Datasets will be published on SwissUBase.

LLMs Disclosure

ChatGPT version 5.0 was used to solve R-coding issues and to validate own interpretation of the model results.

Supplementary Material

Supplementary material for this article is available online in the format provided by the authors (unedited).

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