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Review Article

A Computational Turn in Policy Process Studies: Coevolving Network Dynamics of Policy Change

Maxime Stauffer,[1,2] **Isaak Mengesha**,[1,3] **Konrad Seifert**,[1] **Igor Krawczuk**,[4] **Jens Fischer**,[5,6] **and Giovanna Di Marzo Serugendo**[7]

[1]*Simon Institute for Longterm Governance, Geneva 1207, Switzerland*
[2]*Geneva Transformative Governance Lab, Global Studies Institute, University of Geneva, Geneva 1205, Switzerland*
[3]*University of Amsterdam, WX Amsterdam 1012, Netherlands*
[4]*Ecole Polytechnique Fédérale de Lausanne, Lausanne 1015, Switzerland*
[5]*Université de Toulouse III - Paul Sabatier, Narbonne 31062, Toulouse, France*
[6]*University of Potsdam, Potsdam 14469, Germany*
[7]*Computer Science Center, University of Geneva, Geneva 1205, Switzerland*

Correspondence should be addressed to Maxime Stauffer; max@simoninstitute.ch

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The past three decades of policy process studies have seen the emergence of a clear intellectual lineage with regard to complexity. Implicitly or explicitly, scholars have employed complexity theory to examine the intricate dynamics of collective action in political contexts. However, the methodological counterparts to complexity theory, such as computational methods, are rarely used and, even if they are, they are often detached from established policy process theory. Building on a critical review of the application of complexity theory to policy process studies, we present and implement a baseline model of policy processes using the logic of coevolving networks. Our model suggests that an actor's influence depends on their environment and on exogenous events facilitating dialogue and consensus-building. Our results validate previous opinion dynamics models and generate novel patterns. Our discussion provides ground for further research and outlines the path for the field to achieve a computational turn.

1. Introduction

In the twenty-first century alone, humanity has witnessed many challenges: a global economic crisis, a global pandemic, accelerating climate change, and rapid technological progress. To respond to these challenges, it is essential to better understand how societies can govern intergenerational global public goods. While policy analysis provides detailed accounts of policy effectiveness and guidance on *what* to implement, policy process studies focus on the *how*. It examines the cognitive, behavioral, and social processes that shape and are shaped by the implementation of policies [1, 2]. In short, policy process studies shed light on the determinants of (un)successful collective action.

These processes are notoriously difficult to study, especially quantitatively, because of the paucity of data on actor-level dynamics. As a result, one dominant research agenda in policy process studies, punctuated equilibrium theory, has investigated the patterns of policy change by drawing from available data on policy outputs, such as budget changes and legislation changes [3]. Work on this has identified a policy process "signature:" policy change is primarily incremental and sometimes large and sudden. Its probability distribution follows a power law; a small number of policy changes account for most budget reallocations [4]. This signature is found across cultures in democracies and autocracies, governmental subsystems, as well as regional and international organizations [5].

If such signatures are found, what are the underlying mechanisms that explain their emergence? And do these mechanisms also generalize across contexts? For example, what led international health policy actors to start developing a pandemic treaty in 2021 and not before, despite previous outbreaks and negotiations? Or, what explains the handful of substantial defense budget reallocations made by the US government at the end of the Cold War? Do these explanations share similar features? In a nutshell, which theories and methods allow us to (1) systematically disaggregate signatures into microlevel dynamics, (2) re-aggregate them while accounting for sudden, nonlinear changes, and (3) produce comparative analyses?

Complexity science, pairing complexity theory and, often, computational methods [6], precisely focuses on resolving this micromacro divide found in physical, chemical, biological [7], social and artificial systems [8]. Complexity theory defines complex systems as consisting of many heterogeneous parts whose interactions in networks lead to the emergence of macrolevel outcomes, often nonlinearly [9]. Computational methods enable the formalization of system mechanisms and, through algorithmic processes, provide an understanding of the generation of emergent patterns at the system level [10, 11].

Scholarship has established that policy macrolevel dynamics tend to be nonlinear [4], while policy microlevel dynamics are networked and adaptive [12, 13]. Based on these two observations, various theories of policy processes unite in the view that they satisfy the hallmarks of complex systems [14–17]. Such work has taken a primarily theoretical and qualitative form and made progress on reconciling micromacro dynamics by mapping complex system properties onto the characteristics of policy processes. However, such scholarship has remained abstract and created taxonomies rather than explanations [18]. Its proclaimed advantages lie in "hope rather than experience" (Cairney and Geyer, [19], p. 1).

Mathematicians, computer scientists, and physicists are attracted by the challenge of understanding social phenomena, their potential social impact, and the new challenge of applying their methods to social systems [20]. However, computational methods to understand policy processes remain rare and scattered, often detached from the above literature or mainstream policy process studies. Thus, the scholarship's successful application of complexity science to policy processes, from theory to method, happens in parallel instead of building on previous scholarship. As such, computational contributions often lack realism because they do not engage with ground-level detail provided by specialized scholarship, and thus do not resonate with established policy scholars. The existence of recent exceptions suggests the commencement of a computational turn in policy process studies in its truest sense [21–23]. This paper builds upon those to strengthen this turn.

In what follows, we survey the literature that discusses complexity in policy processes and present an agent-based model of some core policy process dynamics. As one of the current bottlenecks of this computational turn lies in formalizing complexity to investigate it systematically, we focus in this paper on guiding the field from theory to computational implementation. Throughout, we write for both policy process scholars and computational scientists, whose collaboration is important to moving the field forward. We also embed our reflections in the social sciences more widely by drawing parallels with the computational turn that took place in conflict studies throughout the twentieth century [24].

This contribution, and by extension, this computational turn, has historical roots. It can notably be conceived as furthering Herbert Simon's view of policy process studies. Simon contributed pioneering work on the fundamentals of bounded rationality [25], its applications to policymaking [26], the architecture of complex systems [27], the mechanism of preferential attachment in networks leading to power-law distributions [28], and computational methods [29]. His view was hypothesis-driven, based on his empirical observations. He relied on the formalization of complex systems and the study of their unpredictability [30–32]. Except for a handful of scientists [33–35], policy process studies have moved away from Simon's view. Instead, they delved into qualitative and critical analyses [36] or purely rational and therefore simplistic approaches [37]. This paper, like others (e.g., the special issue introduced by Jones and Thomas [38], proposes to re-engage with the early work of one of the fathers of the field to help enrich the study of policy processes going forward.

This paper proceeds in three sections. Section 2 surveys the literature applying complexity science to policy processes. Section 3 presents a baseline policy process model relying on coevolving networks whose results show the emergence of collective dynamics based on individual behavioral rules. Section 4 discusses the model's results as a stepping-stone to improve the application of computational methods to policy process studies. Supplementary information (available here) provides additional details for readers unfamiliar with computational modeling.

2. Complexity in Policy Process Studies: Theory and Methods

Policy processes consist of the interplay between the different forces that characterize policymaking systems. They notably include various policy actors and their surrounding environments that nudge or incentive those actors to behave in a particular way and make choices. Similar to armed conflicts, these dynamics have aroused interest among social scientists because they are characteristic of heterogeneous individuals aligning to take collective action. Where armed conflicts are characterized by individuals who employ violence as a result of the disagreement, policy processes focus on how individuals succeed or fail to agree. The process of figuring out how best to use pooled resources is vital to understand, as it defines the visions of our constitutions, societal narratives, and common goals, specifies the instruments for collective action, and whether its outputs are beneficial to society [39, 40].

Examining policy processes may also increase their legitimacy by fostering transparency and highlighting where they may be broken [41, 42]. As policy processes often involve conflicts of subjective value judgments, objective analyses of the underlying processes can pinpoint reasons for disagreements. Scholars of policy processes have advanced many theories, case studies, and empirical analyses to describe such convoluted phenomena [43]. In this section, we survey how scholars have applied complexity science to study policy processes and sketch current methodological frontiers in addressing the complexity of policymaking.

2.1. Complex Systems Properties. Complex systems satisfy two properties: (1) many heterogeneous, interacting, and adaptive parts that lead to (2) the emergence of system-level patterns [9]. Complexity science attempts to explain such systems by identifying the underlying mechanisms governing such properties, such as identifying the different parts, their interactions, and collective behavior, instead of isolating each moving part or system level (e.g., into micro versus macro) and studying them separately. Below, we discuss both properties in turn.

First, complex systems have many constituent parts. In social systems, such as policy processes, such parts are individuals or groups. These parts can be heterogeneous and have characteristics that vary from part to part. Characteristics of individuals include beliefs, interests, roles, and more. Those components interact with one another. Individuals may interact spatially (e.g., neighbors) or through network structures. Lastly, such parts adapt their behavior as a function of their interactions and environment. Individuals may change their opinions or behaviors as a function of social cues. The described processes characterize the microlevel dynamics of complex systems.

Second, these microlevel dynamics lead to the emergence of macrolevel patterns. Those patterns are defined as "emergent" because they cannot be traced back to the system's constituents [8]. In social systems, an armed conflict, a social movement, or an instance of cooperation cannot be traced back to the position of single individuals but is the product of their interactions and relative positions. Moreover, those patterns may be nonlinear. That is, a small change at the microlevel may have a significant effect at the macrolevel and vice versa. Armed conflicts and opinion dynamics are nonlinearities. Negative or positive feedback loops absorb or amplify information cascades and can lead to conflict outbreaks [44] or shifts of popular opinion [45–47].

On top of these two properties, complex systems often feature other processes. One example is self-organization. It is a process where the emergence of macrostructures results from interactions between many parts, with the absence of central control or interventions. In social systems, this would mean that narratives or group decisions cannot be attributed to single agents but rather to the structures crystalized by social interactions [10]. Another example is path dependence: macrostructures tend to be heavily contingent on the past. Previous structures constrain the set of possible future systemic states. In social systems, the evolution of laws and institutions are good examples of path dependence. They set directions or rules that future social interactions run on to evolve into other states [48, 49].

2.2. Intellectual Lineage: Policy Processes as Complex Systems. There is an intellectual lineage among scholars of policy processes regarding their conceptualization as complex systems. They, however, do not always do so explicitly [14], or in the same way [50]. They sometimes propose other frameworks that broadly rely on the same ideas but without using the language of complex systems or using complexity theory for various purposes. In what follows, we categorize and describe three streams of literature that define this lineage. The first stream implicitly uses complexity theory and does not provide modeling attempts. The second stream explicitly applies complexity theory, but only theoretically and abstains from modeling. The third stream explicitly applies complexity theory to policymaking and attempts to model processes, often detached from predominant policy process theories. Table 1 summarizes these three streams.

To conduct our survey, we selected literature that pertains to policy process studies and not policy analysis. Our literature selection was based on three criteria. First, we selected reviews of the theories mentioned in Weible and Sabatier [43]. Several of these theories build on concepts related to complex systems (e.g., multiple agents, networks, nonlinearity, or critical points). We selected reviews to ground ours in a larger body of references and theoretical applications. Second, we searched for literature that mentions policymaking AND "complex systems" OR "computational model." Third, we excluded references that treat policy consequences only. The search was not meant to be exhaustive but serves to illustrate the intellectual lineage in the literature. We did not discuss Gilbert et al. [82] because this contribution focuses on modeling the consequences of policies. Our paper focuses on processes that lead to the formation of policies. While we agree that this distinction between policy process studies and policy analysis has limitations, we assume that policy processes exhibit different dynamics than the systems in which policies are implemented. Moreover, the use of complexity theory and its methodological counterparts in policy analysis is much more frequent than in policy process studies.

2.2.1. The Implicit Use of Complexity in Policy Process Theories. First, the implicit use of complex system properties lies in the most common theories of policy processes, as reported in the work of Weible and Sabatier [43] and illustrated by references 1–7 in Table 1.

The advocacy coalition framework defines the coevolution of coalitions as a function of their interactions and the resulting adaptation of individuals' beliefs [57]. The multiple streams framework characterizes policy processes as consisting of different flows of activity that, when coupled, can lead to drastic, sudden changes at the system level. This coupling is often due to the behavior of a small group of actors and changes in policy environments [55, 83]. The policy feedback theory conceptualizes feedback loops from policies to policy processes, thus theorizing amplification or

Table 1: Literature applying complexity science to the study of policy processes. Stream 1 (1–7) applies complexity science implicitly and conceptually. Stream 2 (8–26) applies complexity science explicitly and conceptually. Stream 3 (27–41) applies complexity science together with formal modeling.

#	Reference title	Reference number	Implicit or explicit use of complex system	Type of contribution	Contribution	Formal modeling
1	Agenda dynamics and policy subsystems	[51]	Implicit	Theory	Conceptualize abrupt policy changes whose emergence happens from the interactions of multiple adaptive agents. Cite complex system literature [52]	NA
2	Agendas, alternatives, and public policies	[53]	Implicit	Theory	Conceptualize policymaking through multiple streams but discuss complexity theory in chapter 10 as a potential framework that can explain sudden, nonlinear change in policymaking	NA
3	Policy feedback theory	[54]	Implicit	Theory	Describe feedback loop between policy outcome and policy processes	NA
4	A river runs through it: a multiple streams metareview	[55]	Implicit	Theory; review	Describe interplay of actor and environment to explain policymaking; report 88% of studies are qualitative	NA
5	Policy learning and policy Change: theorizing their relations from different perspectives	[56]	Implicit	Theory; review	Describe adaptive behavior of individuals and groups	NA
6	Common approaches for studying advocacy: review of methods and model practices of the advocacy coalition framework	[57]	Implicit	Theory; review	Describe the use of coevolutionary coalitions to explain policy processes; report that 70 to 100% of analyses are qualitative	NA
7	Punctuated equilibrium theory: explaining stability and change in public policymaking	[3]	Implicit	Theory	Describe power-law in budget changes and theorize positive and negative feedback loops at the microlevel	NA
8	Nonequilibrium theory and its implications for public administration	[58]	Explicit	Theory	Conceptualize policymaking and public administration through the lens of dynamic and nonequilibrium systems	NA
9	Managing uncertainties in networks a network approach to problem solving and decision making	[59]	Explicit	Theory	Conceptualize policymaking as set of networks and where policy change depends on the adaptation of networks to exogenous events	NA
10	Governance, complexity, and democratic participation	[60]	Explicit	Theory	Apply complexity theory to policymaking in urban environment, both understand processes and consequences	NA
11	Managing complex governance systems	[61]	Explicit	Theory	Collect frameworks that apply complexity theory to policymaking, notably nonlinear dynamics, self-organization, and coevolution	NA
12	Complexity theory and evolutionary public administration: a sceptical afterword	[18]	Explicit	Theory	Formulate a criticism of the current scholarship that applies complexity theory to policy processes and delineates avenues for further research	NA

Table 1: Continued.

#	Reference title	Reference number	Implicit or explicit use of complex system	Type of contribution	Contribution	Formal modeling
13	Complexity and public policy: a new approach to twenty-first-century politics	[15]	Explicit	Theory	Map properties of complex systems on the characteristics of public policy processes and discuss implications	NA
14	Complexity, institutions, and public policy	[62]	Explicit	Theory	Apply complexity theory to institutionalism and discusses how this lens can help understand policy processes and as well as a policy evaluation	NA
15	Complexity theory in political science and public policy	[14]	Explicit	Theory	Discuss the use of complexity to understand policy processes and implications for the field	NA
16	What is evolutionary theory and how does it inform policy studies	[63]	Explicit	Theory	Discuss the use of evolutionary theory in policy process studies and present complexity theory as one approach	NA
17	A complexity theory for public policy	[16]	Explicit	Theory	Map properties of complex systems on the characteristics of public policy processes and discuss implications	NA
18	Complexity theory and its evolution in public administration and policy studies	[64]	Explicit	Theory	Survey the evolution of the application of complexity theory and proposes a four-stage model of such developments	NA
19	The emergence of complexity in the art and science of governance	[65]	Explicit	Theory	Discuss applications of complexity theory to governance and propose methods to put concepts to the test	NA
20	How the complexity sciences can inform public administration: an assessment	[66]	Explicit	Theory	Discuss major books published on complexity theory and public administration and public policy and delineate common themes	NA
21	Handbook of complexity and public policy	[67]	Explicit	Theory; review	Provide an overview of the use of complexity theory to explain policy processes, and describe the use of agent-based models	NA
22	Agile actors on complex terrains: transformative realism and public policy	[68]	Explicit	Theory	Apply ideas from complexity theory to public policy, including both policy processes and policy consequences	NA
23	Complexity thinking in public administration's theories-in-use	[69]	Explicit	Theory	Survey the use of complexity theory in public administration and how it is linked (or not) to established theories	NA
24	A critical discussion of complexity theory: how does "complexity thinking" improve our understanding of politics and policymaking?	[19]	Explicit	Theory	Survey applications of complexity theory and formulate a critique that they so far have are driven by hope rather than experience, and claim that complexity theory can serve as a bridge to communicate better between researchers and practitioners	NA
25	The new policy sciences: Combining the cognitive science of choice, multiple theories of context, and basic and applied analysis	[1]	Explicit	Theory	Cover briefly how complexity theory fits in the policy sciences	NA

Table 1: Continued.

#	Reference title	Reference number	Implicit or explicit use of complex system	Type of contribution	Contribution	Formal modeling
26	Complexity theory in public administration	[70]	Explicit	Theory	Provide an overview of the latest discussions and applications of complexity theory to public administration, with content covering both policy processes and policy analysis.	NA
27	Adaptive parties in spatial elections	[71]	Explicit	Exploratory modeling	Model dynamic voting behavior between adaptive parties, with an unclear link with policy process theories	Agent-based model
28	Political complexity: nonlinear models of politics	[72]	Explicit	Review of models	Provide an overview of models of politics, with unclear links to policy process theories	Various
29	Abstention in dynamical models of spatial voting	[73]	Explicit	Exploratory modeling	Model dynamic voting behavior between adaptive parties, with an unclear link with policy process theories	Mathematical model
30	Mixing beliefs among interacting agents	[74]	Explicit	Exploratory modeling	Provide a model of opinion dynamics in networks of agents	Mathematical model
31	Policy and the dynamics of political competition	[75]	Explicit	Exploratory modeling	Conceptualize policymaking through an agent-based perspective on party competition where agents are adaptive and various processes are used to generate emergent policy change, with weak links to policy process theories	Agent-based model
32	Computational methods and models of politics	[76]	Explicit	Review of models	Review of models of politics, mostly focusing on electoral systems and institutional design	Agent-based model
33	A tournament of party decision rules	[77]	Explicit	Exploratory modeling	Conceptualize policymaking through repeated games with adaptive parties running for elections	Agent-based model
34	Sociophysics: a review of Galam models	[78]	Explicit	Review of models	Review 25 years of modeling attempts to understand democratic voting, decision-making fragmentation and coalition, and opinion dynamics	Mathematical models
35	MASON RebeLand : an agent-based model of politics, environment, and insurgency	[79]	Explicit	Exploratory modeling	Formalize a large-scale agent-based model with an unclear link to policy process theories	Agent-based model
36	Simulating political stability and change in The Netherlands (1998–2002)	[80]	Explicit	Emp.-validated modeling	Implement a version of Kollman et al. [71] model and test it empirically	Agent-based model
37	Understanding collective decision making: a fitness landscape model approach	[21]	Explicit	Emp.-validated modeling	Present a model of collective decision-making using fitness landscapes and apply the model to empirical cases; reconcile micro and macrodynamics of how groups agents interact to solve collective problems	Fitness landscapes
38	Deep learning and punctuated equilibrium theory	[22]	Explicit	Exploratory modeling	Model patterns of policy attention	Deep neural networks
39	Policy emergence: an agent-based approach	[23]	Explicit	Exploratory modeling	Formalize an agent-based model based on the combination of policy process theories	Agent-based model

Table 1: Continued.

#	Reference title	Reference number	Implicit or explicit use of complex system	Type of contribution	Contribution	Formal modeling
40	Modeling contagion in policy systems	[35]	Explicit	Exploratory modeling	Model attention contagion in policy networks, with a clear link to policy process theories	Agent-based model
41	Association between decisions: experiments with coupled two-person games	[81]	Explicit	Exploratory modeling	Provide a game-theoretic model to explore decision-making between agents that meet in coevolving policy arenas	Game-theoretic model

absorption dynamics between the products of policy processes and their inner workings [54]. Policy learning defines the dynamics of continuous adaptation of networks of policy actors as a function of new information, thus portraying the adaptive capacity of the participants in policy processes [56]. Last but not least, punctuated equilibrium theory empirically identifies power laws in budget changes and theorizes mechanisms of inertia and sudden change based on positive and negative feedback loops within microlevel processes [3].

These theories reach the view that policy processes consist of bounded-rational, attention-limited (thus adaptive) actors whose interactions lead to system-level outcomes such as policies. The presented theories have been applied to numerous case studies and seem applicable in both democratic and authoritarian political contexts [84]. Comparative studies in punctuated equilibrium theory, for instance, have found empirical regularities across almost all democracies, as well as China and international organizations [4, 85, 86]. Overall, the literature has progressed in understanding micro and macrolevel dynamics [32]. Our supplementary information (available here) provides additional discussions of the methods, mostly qualitative, used by this stream of literature.

It is important to note that, in the early 1990s, scholars behind these theories also made explicit reference to complexity theory as a way to explain sudden, nonlinear changes. For example, Baumgartner and Jones [51] cite complexity literature [52], and Kingdon ([83], chapter 10) discusses complexity theory as a potential framework to conceptualize policy processes. Therefore, it is plausible that these theories of policy processes rely on complexity theory, explicitly for their authors but implicitly for their readers. Policy process scholars may be aware of developments in other disciplines, such as complexity theory applied to other social sciences, but they may describe theoretical innovations without necessarily referring to complex systems. This choice may be explained by complexity theory, being a general theory that, once applied, might be termed differently. Or, scholars may want to increase their chances of passing peer-review for more traditional academic journals and thus avoid explicit reference to non-mainstream theories [66].

2.2.2. The Explicit and Theoretical Use of Complexity in Policy Process Studies. Second, a small group of scholars has explicitly explored the application of complexity to policy processes, as shown by references 8–26 in Table 1. They define policy processes as networks of policy actors who have different personal characteristics and participate in an informal and formal collective decision-making process. This process involves erratic features linked to the ideas of emergence and nonlinearity, and thus complexity. The emergent properties are either coalitions, agendas, policies, or decisions.

After his first main contribution [58], Kiel proposed four stages of the development of this literature [64]: emergence (1989–1998), convergence (1999–2002), proliferation (2003–2014), and divergence (2014-future). While it is true that this stream of literature has proliferated in the early 2000s and the 2010s, as evidenced by multiple special issues [38, 87, 88], it has not yet reached a point of divergence. Instead, scholars have been going through a process of iteration, applying complexity theory to various parts of policy processes [15, 59, 61, 62] and questioning each other's contributions [19, 66]. Book reviews provide particularly illuminating discussions of the field [89–91].

Pollitt's criticisms (2009) of the use of complexity theory in policy process studies describe the state of this literature and still seem applicable today. "(complexity theory) tries to be all things to all men, a bit of positivism, a bit of postpositivist critical realism, and a bit of social constructivism." (Pollitt [18], p. 229). He claims that proponents of complexity theory in policy processes have primarily developed conceptual taxonomies rather than hypothesis-driven propositions. He contends that scholarship must move beyond theory and case studies and consider other methods to adequately employ complexity to generate valid explanations of policy processes [18].

In their assessment, Gerrits and Marks [66] report that publications on complexity theory and policy processes have multiplied fivefold between 2005 and 2013, with authors having published books rather than articles and in niche journals rather than mainstream policy journals. As a response to Pollitt [18]; they claim that the recent books have converged regarding the core themes they treat. In discussing Morçöl's seminal book [16], Gerrits points out that the book does not address Pollitt's critique on moving away from taxonomies and applying complexity theory with its methodological counterparts [89]. Supplementary information (available here) provides additional discussions of the methods used by this stream of literature.

Overall, scholars use complexity theory for three different goals. Some see the value of complexity theory as a way to recognize unpredictability [19]. Others want to better understand policy processes through a unifying lens [16]. A last group of scholars uses complexity theory as one valuable input, which needs adaptations once applied to empirical cases [92]. The computational turn advocated in this paper is in line with the last goal.

2.2.3. The Explicit and Formal Use of Complexity in Policy Process Studies. Third, a handful of scholars have been trying to apply and model complexity in policy processes explicitly and formally, as illustrated by references 27–41 in Table 1. Overall, their contribution subscribes to the view that the usefulness of complexity theory extends beyond recognizing unpredictability and that the theory must undergo necessary adaptations when applied to empirical cases.

This work was initially pioneered by Kollman, Miller, and Page [71]; and others have followed suit, often detached from the rest of the literature on policy processes and in various directions [73, 74, 77–80]. More recently, a small group of scholars has been trying to push the frontier by modeling policy processes in ways that combine complexity theory and more mainstream theories of policy processes. In so doing, they can translate mainstream theories into a series of propositions that allow algorithmic thinking and thus computational modeling.

This work follows what complexity scientists have applied to other social sciences: explicit and formal modeling [93–95]. For instance, Geritts and Marks [21] reconcile micro and macrodynamics in collective decision-making using fitness landscapes. Thomas [35] developed an agent-based model of attention contagion. Klein [23, 96] proposes a model that integrates multiple streams and the advocacy coalition framework. Marks et al. [81] offer a game-theoretic model of collective decision-making where agents meet in coevolving policy arenas. This progression is promising as, previously, quantitative models were statistical (i.e., data modeling). In contrast, network- and agent-based models formalize not just observations but the mechanisms that produce them.

Another line of progress lies in deep learning models using decision trees and forest fire dynamics to replicate power-laws in budget changes and link them with microlevel processes [22, 97]. While in their infancy, these models, network, agent-based, and deep learning, are increasingly connected to policy process theory and thus illustrate the computational turn that must go hand in hand with established scholarship. However, to date, these models have not generated significant insights beyond unpacking the barriers to computational modeling of policy processes. They are also published in journals poorly known to policy process scholars. In the rest of this paper, we propose avenues to strengthen this computational turn.

3. Modeling Policy Processes as Coevolving Networks

In this section we present the implementation and results of a baseline model of policy processes. The reader can refer to the supplementary information for an introduction to computational modeling.

The primary purpose of the following model is to respond to the formalization bottleneck identified in the literature review: applications of complexity science to policy process studies are either conceptual or, when using computational methods, detached from policy process theory. Therefore, we present a simple model as a consistency proof for given assumptions and mechanistic explanations provided by policy process theory. This work is necessary to bring about a computational turn and leverage complexity science in the study of policy processes. As such, the following does not attempt to predict and resolve policy process hypotheses, but rather provide the basis that future modeling attempts can build upon.

Our paper is akin to what Epstein [98] or Clauset and Gleditsch [99] contributed to the field of conflict studies: formalizations of core assumptions to test their realism and consistency with theoretical conclusions. We emulate this approach by outlining a general model of policy processes.

3.1. Model Conceptualization. Our model conceptualization is based on the common denominator of four established policy process theories. The advocacy coalition framework (ACF), multiple streams framework (MSF), punctuated equilibrium theory, and policy learning all share the view that policy processes consist of (1) adaptive, bounded-rational agents whose (2) interactions in networks lead to (3) the formation of clusters of opinion/attention and (4) periods of stable, incremental policy change and periods of sudden policy change. ACF and MSF also assert the importance of policy brokers or policy entrepreneurs, who are well-networked agents with high social acuity who instrumentalize exogenous events or windows of opportunities to shift policy networks' attention or align coalitions' opinions. Multiple case studies and refined theory substantiate this conceptualization. Out of these four theories, our conceptualization is very close to the advocacy coalition framework, which has been proposed as a potential umbrella policy process theory [100].

By formalizing the four components above, we aim to find contradictions or a logically consistent description of them, and thus a formal basis for the above theories. Hence, our working hypotheses are the following: assuming (1) and (2) and some mechanism that attributes "political capital" will result in:

(a) the observation of (3) and (4) as emergent behavior; and

(b) the emergence of agents that take the role of policy entrepreneurs.

Fundamentally, this conceptualization follows the logic of coevolutionary networks or adaptive networks [8]. In other words, the topology of the network influences the local dynamics of the system and vice versa (Figure 1). This creates a feedback loop between opinion dynamics and network dynamics over time [101]. When applying this logic to policy processes, actors' capabilities are largely dependent on their environment, and actors can simultaneously significantly influence and shape their future environment. Translating the four components above into the logic of coevolving networks is a starting point to provide an algorithmic understanding of policy processes. This algorithmic understanding is the premise we use to specify a baseline agent-based model that can be implemented computationally. Proceeding this way allows us to develop a model that can verify stylized facts from the literature.

3.2. Model Specification. Firstly, we specify the necessary components and implementation of our baseline model of policy processes. Then, we will provide justification for our specific design choices. In this baseline model, we consider a fixed population of N interacting agents. They are initially embedded in a scale-free Holme-Kim network which is subject to local rewiring mechanisms of agents [102]. We have implemented the model in discrete time, where the agents are all activated in random order each time step. However, not all agents become active every single time step. We draw the activation intervals for each agent from a truncated Poisson distribution. As a consequence, each agent becomes active at every i steps. The differences in activity are simple, yet potentially important for the microscopic explanation of punctuated equilibria in the decision-making process. There is no clear distinction between different strategies, but rather a homogeneously populated spectrum of strategies. We condense the space of possible actions each agent has to three different types of fundamental actions:

(1) Improve network centrality (rewiring): given the clustered nature of social networks, the agent predominantly attempts to form a new connection with the set of neighbors (denoted with $n_i^{(2)}$). The agent prefers individuals with a higher network centrality. This means the probability to connect with the agent i is proportional to the centrality of i.

(2) Gather support (rewiring): similarly, the agent assesses the opinions of other agents in $n_i^{(2)}$ and attempts to establish a connection. Agents will optimize to have strong ties to their peers within their "coalition". At the same time, they aim to have a small fraction of connections with the "other side." Consequently, the agent increases/decreases connections with agents of other opinions, should its own neighborhood be too homogeneous/heterogeneous.

(3) Influence others (opinion dynamics): agents aim to homogenize their direct neighborhoods n_i by attempting to persuade one neighboring agent to update its opinion in the direction of their own. Here we deploy a replicator dynamics scheme, where behavior (here opinion) is updated depending on fitness (here political capital). The neighbor is chosen randomly and within a certain distance from the opinion (i.e., bounded confidence).

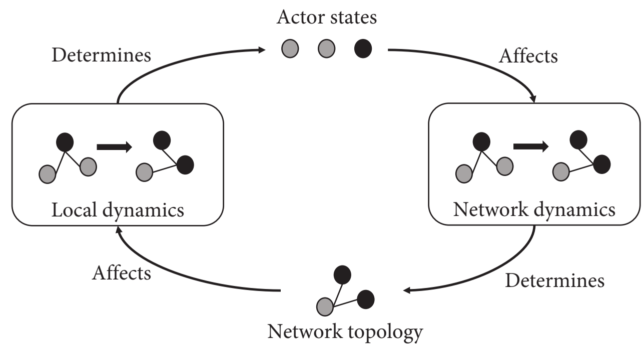

Figure 1: Logic of coevolving networks.

The successful implementation of all the above strategies is dependent on the fitness (i.e., political capital) of our agent. However, we do allow a small probability for random connections/opinion changes to occur. The success rate $s \in [0, 1]$ is a linear function of the political capital $s = s(PC)$. It specifies the effectiveness with which agents pursue their strategy, which in turn influences their PC in the future. Thus, we are implying that (a) the fitness landscape is a global property of these systems and (b) the fitness landscape is fixed over time. Both of which are strong assumptions that might need adjustment in future work. Lastly, we want to define how the PC for agent i is computed:

$$PC_i = \alpha_i \cdot \beta(n_i) \cdot \gamma(n_i). \tag{1}$$

With n_i as the neighborhood of agent i, and $\alpha_i \in [0, 1]$ the normal distributed capability. The other components are functions of the agent's environment, i.e., their neighborhood n_i. Here we denote $\beta(n_i) \in [0, 3]$ as the support function and $\gamma(n_i) \in [0, 3]$ as centrality function. The support function computes the average opinion distance $x = |\overline{n}_i - i|$ and returns the value of the beta-distribution $\mathscr{B}(2, 3)$ at that location. The centrality function is computed by rank ordering the betweenness-centrality of all agents, based on the position of the agent i. With $x =$ rank/agents, it computes the influence based on centrality from an exponential distribution with $f(x, \lambda) = \lambda e^{-\lambda x}$ and $\lambda = 3$. They are multiplicative because they are all necessary for influencing the policy process. Should either one be close to zero, the agent's chances of successfully shaping this process will be slim. The precise choice for the hyperparameters follows our best understanding of these processes but ultimately remains a somewhat arbitrary choice. Therefore, we need to include them in our sensitivity analysis (c.f. supplementary information (available here)), given the importance of the "fitness function" on the overall coevolutionary dynamics. Figure 2 depicts this crucial role in the dynamics.

The basis of the implementation builds on three previous models of policy processes [21, 23, 35], which formalize the network-dependent adaptive behavior of policy actors. We also draw from a simple model of opinion dynamics (see supplementary information for a discussion thereof) [103]. However, our model is simpler than Thomas [35] and Klein [23] in its formalization because of our use of more compressed functions than a large set of additive functions. Yet, this simplicity arguably allows for more complexity as policy process dynamics are likely not additive. Moreover, our model could plausibly be more realistic than Gerrits and Marks [21] because of our agents' short-term fitness function (PC). In contrast, Gerrits and Marks [21] suggested modeling adaptive agents through fitness landscapes where the agents' fitness depends on their success to pass the solution they want. As "passing solutions" is a "rare" event in policy, we decided to model agents according to their short-term, instrumental heuristics, which they use to achieve their higher-level policy goal. This logic draws from the literature on the strategies of policy entrepreneurs [104]. That said, the frequency of passing policies, the relevance of heuristics as well as the payoff of agents all depend on the timescales we decide to investigate. Ultimately, our model examines the short-term dynamics of policy processes by focusing on behaviors over six to thirty-six months.

The proposed model is focused on one single policy problem and a fixed number of actors. These assumptions are convenient but unrealistic given that policy actors often handle multiple problems at once and that actors enter and leave the policy arena continuously. We correct these assumptions by allowing actors to act at different timescales. This decision incorporates the idea that not all actors work on one problem at the same intensity (because they handle other problems elsewhere) and that actors enter into or disengage from policy processes.

In the proposed model, agents attempt to build ties with agents that share similar opinions as well as agents who more clearly disagree. While opinion dynamics models [78] tend to primarily focus on the former, we think that this assumption is more realistic for modeling policy processes. First, building ties with people who disagree is a way to receive information about how they think and thus learn from them. Second, policy change ultimately depends on policy actors' changing their minds as a result of interactions. Thus, to be influential, policy actors need ties with people with different opinions to have the opportunity to change their minds. Third, policy actors might work with actors they disagree with in order to optimize for long-term political survival (i.e., receiving favors in return later) [105]. Fourth, actors may connect with actors they disagree with on one subject because they agree on another subject. Therefore, allowing agents to connect with others they disagree with is a way to integrate some multidimensional problem dynamics.

Overall, the above model fuses ideas from policy process theory on the one hand and modeling theories on the other hand. We believe this choice makes sense because policy processes can be conceptualized through the combination of information theory (see information processing [106] or learning [56]); decision theory network theory; sometimes game theory (mostly repeated games [93], where agent traits evolve as a function of interactions).

3.3. Results. We implemented the baseline model in *Python* and analyzed its behavior. In order to answer hypothesis (a), we chose to observe the opinion dynamics of the baseline model, while the evolution and accumulation of "political capital" (PC) is used to investigate hypothesis (b).

We observe the classical opinion dynamics of a bounded confidence model. As an emergent behavior of our system, we observe the formation of clusters (i.e., coalitions) whose basin of attraction covers most of the opinion space. However, due to the additional network dynamics, these groups do not separate as clearly as the classical bounded confidence model [103]. Instead, we observe a small but significant number of actors that navigate between coalitions and attain often semistable and central positions with respect to opinion and network topology. Consequently, the system seems to be bistable, with a semistable coalition-state and a stable converged state (see Figure 3(c)). Note that we did not include any polarizing forces in this baseline model and therefore cannot expect polarizing behavior that would move formed coalitions away from each other.

In Figure 3(a) we can see the cumulative political capital (PC) over time. It becomes quite clear that PCs are distributed very unevenly, with a small number of agents aggregating most. Despite allowing agents to rewire according to their individual strategies, we can see in Figure 3(a) that some agents maintain a very central position for long periods of time.

Lastly, in Figure 3(c) we can see the opinion dynamics for two runs with the same seed of the model. The colored lines depict the individual opinions of the baseline dynamics, which exhibits coalition forming. The grey lines show the effects of a "focusing event" [107], meaning that some external reason draws more attention and therefore more activity to the problem for a limited period of time. We implemented this event by setting the activation frequency to one for every agent and slightly increasing the bounds for considered opinions to influence others from 0.1 to 0.2 for 200 time-steps. As a result, opinion convergence is accelerated, or the semistable "fixed-coalitions" state is disturbed, initiating the convergence toward a compromise. Interestingly, we observe some reshuffling after the event as well. Coalitions are being restructured until, ultimately, consensus is reached.

4. Discussion

4.1. Interpretation of Results. Of course, this baseline model is very reductionist in nature. The results are partly intuitive, for example in the case of the opinion dynamics, given previous well-understood models [74, 78, and 103] and the advocacy coalition framework [57]. They are partly surprising considering the stability of actors with respect to political capital. Nevertheless, they are thought-provoking for our conceptualization of policy processes and initially formulated hypotheses.

For example, in Figure 3(b), we observe large jumps in political capital, whereas only a small number of agents are responsible for most spikes. One interpretation of this might be that in our model, instead of exerting lots of influence constantly, highly influential agents are rather more likely to seize windows of opportunity. This implies that there are conditions that can make agents very influential, but these are highly dependent on the environment. More generally, the policy process seems to be, at least partially, driven by

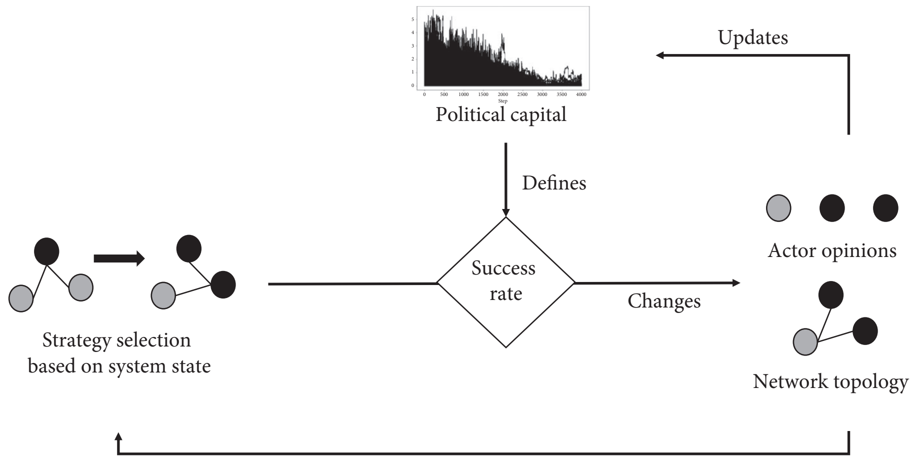

Figure 2: Model flow (agent-level).

arising opportunities rather than the behavior optimization of agents themselves. This result may be consistent with the early ideas advanced by Simon [26] and later by theories of ecological rationality [108], where agents' rationality depends on how they adapt to their environment. Influential agents may thus be the ones who can take more efficient social shortcuts more frequently than those who are consistently dominant.

Likewise, we can interpret the occurrence of "focusing events" as fostering dialogue and accelerating or initiating convergent behavior. Increased activity alone seems insufficient in explaining punctuated equilibria in our conceptualization of policy processes. This observation may be consistent with the idea that "focusing events" urge actors to find a solution and lead influential agents to employ their shortcuts to create compromises [109], an idea analogous to propositions made by the multiple streams framework (MSF) [55] and by punctuated equilibrium theory [3].

Consequently, we can partly refute/validate hypothesis (a), as punctuated equilibria require additional conditions to emerge (e.g. exogenous shocks) while we do observe cluster formation and periods of stable/incremental policy change. Clearly, we could substantiate the existence and relevance of policy entrepreneurs and therefore validate hypothesis (b).

4.2. Model Extensions. Clearly, a more extensive analysis of this baseline model is needed. Some experiments include investigating the influence of path dependencies or searching for evolutionary stable strategies, for example, through Moran processes [110]. But, of course, some of our fundamental assumptions might be put into question. Therefore, it is valuable to incorporate criticism of our approach as early as possible. Given the plethora of problem dimensions, agent properties, and institutional processes, there is no lack of possible extensions of the model. At the same time, the tension between the realism that is demanded by policy scholars and the reductionism that is needed to formalize mechanisms will endure. This tension can form the basis for productive discussions focused on reducing ambiguity and explicitly stating assumptions in order to foster criticism and refinement in policy process studies.

First, we would increase the dimensionality of the opinion space and let the attention between them follow existing models of attention dynamics [46, 111]. Second, we need to investigate local rules that can account for polarization [112]. Additionally, investigating a consistent framework for punctuated equilibria to emerge and the necessary conditions thereof would provide valuable insights if any of the different frameworks (e.g., ACF or MSF) are mutually exclusive. Third, incorporating more clearly the institutional rules governing adaptive policy networks, such as election cycles or voting procedures, might shed light on interesting dynamics of collective adaptation to key policy events. Lastly, the systems of interest are embedded in a larger socio-economic landscape that introduces exogenous forces into the policy process. A modeling approach allows us to explore these interactions in a rigorous manner.

4.3. Notes on Formalizing Policy Processes. We want to emphasize the utility of computational approaches in these systems. We were able to put our best understanding of a specific subdomain of policy processes under scrutiny. Meaning, we were able to show rigorously what follows from our assumptions, and what does not. This provides a consistent proof, and should the assumptions be justified, a sufficient (mechanistic) explanation for certain observations $\mathcal{O}$. In order to provide the necessary conditions for observing $\mathcal{O}$, one needs to exclude other possible mechanistic explanations. However, in the case of agent-based modeling, this can only be achieved through adequate verification and validation procedures. Once they are established and verified, we can begin to increase complexity and explore the hypothesis space of policy processes increasingly freely. Similar to neurobiology, by interpreting the individual as a neuron in the organism that is the policy process, our goal

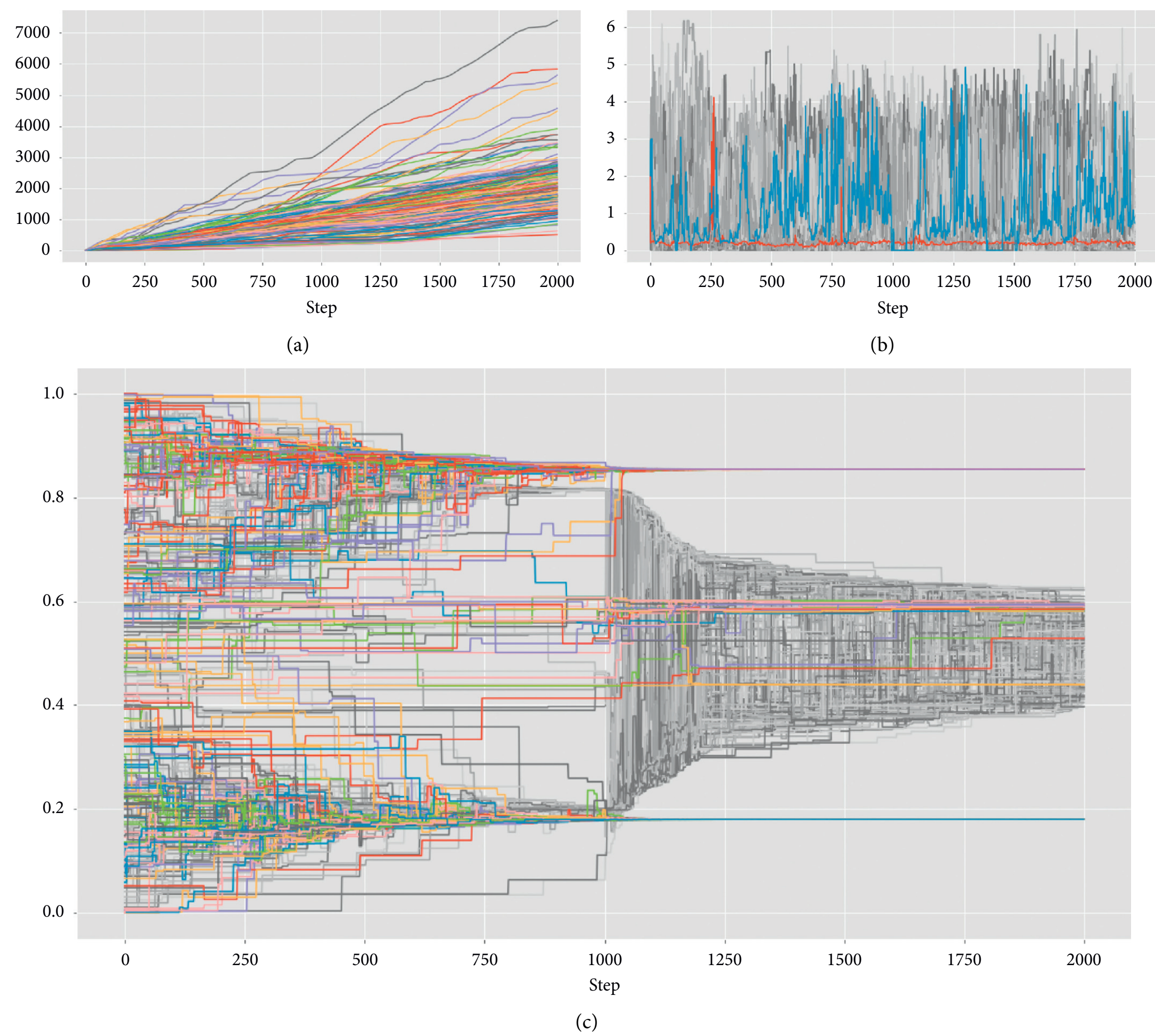

Figure 3: Behavior of baseline model: (a) cumulative PC of different actors over time, (b) PC over time with two highlighted individuals, and (c) opinion dynamics with (grey) and without (colored) focusing event. The focusing event started at time-step 1000 and lasted for 200 steps. During which all agents became more active and the convergence parameter was increased from 0.1 to 0.2. See the supplementary material for all model parameters of this simulation.

must be to trace most of its emergent effects back to it. All future models (or extensions) should target the properties or interaction rules of the individual. Environmental conditions and events should, if possible, be formulated at the microlevel description of the system.

4.4. Research Directions to Advance a Computational Turn in Policy Process Studies. The baseline model above illustrates the type of hypothesis-driven contributions that a computational turn may provide to policy process studies. Should scholars of the field engage with that turn, we expect the following three avenues of progress to manifest.

First, as things stand, the literature on policy processes has identified a robust power-law of public budgets, which is a decent proxy for policy change [4]. The same literature has identified drivers of political behavior and policy networks [32]. Yet, both streams are somewhat detached from one another [35]. Ontologically akin to Schelling's work on micromotives and macrobehaviors [113], we expect a computational turn to reconcile the micro and macrolevels and provide empirical explanations of how policies change as a function of small changes at the microlevel. While public budgets depict empirical regularity across contexts [3], the driving mechanisms may be contextually different [84, 114]. Moreover, the formalization of complex policy processes will also enable the exploration of a large set of correlates and test the sensitivity of initial conditions (e.g., network structures), the formation of coalitions, and the effects of exogenous perturbations.

As such, this avenue looks very similar to the computational developments in the study of armed conflict. A power-law of the frequency and severity of conflict was discovered in the middle of the twentieth century and has been confirmed over time [115, 116]. In parallel, other scholars have theorized the mechanisms of interstate and intrastate armed conflicts [117]. Only very recently have empirically valid computational models formalized microlevel dynamics and generated validated power-laws of conflicts [44, 118].

Second, reconciling microlevel dynamics and macrolevel outcomes computationally and empirically can allow the exploration of levers [119] for policy change. For instance, how does shifting information provision (e.g., increasing information quantity in the system) compare to shifting information processing (e.g., allowing actors to process more or less information) versus changing network structures (e.g., clustering or declustering networks) versus changing rules (e.g., incentives and reward structures) [107, 120]?

Third, the examination of those different levers within formal models can shed light on how to intervene in policy processes. Therefore, the ultimate contribution of computational policy process studies could be to generate evidence-based recommendations to reform policy processes such that they better account better for the bounded rationality of policy actors, the collective nature of their processes, their changing and information-rich environments, and their inherent ambiguity. For example, which mechanisms can install the right feedback loops to foster an adequate division of power and better participation in decision-making?

The proposed research avenues characterize a computational turn in policy process studies. However, this turn does not imply the dominance of computer scientists, mathematicians, and physicists within the social sciences. Historians, philosophers, and political scientists do need to contribute their knowledge. The idea is to combine their questions, insights, and conceptualizations with the methods and ways of thinking from the computational sciences. Computational methods must also become more prominent in the curriculum of social scientists. The publication outlets for this work must also become renowned policy process journals instead of niche modeling journals. This computational turn is a truly interdisciplinary project aiming to better understand the dynamics of collective action. As such, it is itself a collective endeavor that must aggregate the insights of various perspectives. Computational policy process scholars will have to drink their own medicine.

5. Conclusion

What are the determinants of (un)successful collective action? Over the past three decades, scholars have implicitly or explicitly relied on complexity theory to describe the reality of policy process dynamics. However, scholarship using the methodological counterparts of complexity theory, such as computational models, is rare and often detached from mainstream theories. Current attempts to employ complexity science as a whole to examine policy processes from theory to method happen in parallel and separate to the literature and thus do not speak to established journals and scholars. This paper aims to correct course and advance a computational turn in its truest sense by pairing mainstream policy process theory with complexity science.

We propose a baseline policy process model that relies on the common denominators of four established policy process theories. Building on previous modeling attempts, we offer an implementation of the model by using coevolving networks, where agents adapt their opinions and strategies as a function of their networks and the opinions and strategies of others. This simple, algorithmic approach elegantly encapsulates the dynamics of policy processes and generates emergent patterns such as the formation of coalitions and the influence of key actors. The model suggests that an actor's influence is limited more by arising opportunities than by engaging in optimizing behavior. Another result shows that exogenous events can speed up dialogue and consensus-building. These emergent properties that stem from explicitly behavioral rules at the agent level show some consistency with previous theory. While this model is not empirically validated, it offers an illustration of how to maneuver the step from conceptualization to implementation, often overlooked by policy process scholars, and provides fertile ground for further research. A computational turn can motivate the creation of various models based on different assumptions whose results can serve as comparative analyses and thus hypothesis falsification.

We identify three contributions that a computational turn in policy process studies can help deliver. First, computational models may validate specific propositions that reconcile microlevel dynamics and macrolevel outcomes. Second, they can help identify leverage points that lead to sudden policy changes or set path dependencies. Third, their results can offer avenues for mechanism design to reform policy processes and contribute to more effective institutions. These contributions illustrate what sets a computational turn apart from the purely theoretical use of complexity science in policy process studies: a focus on falsifying hypotheses by leveraging methods that allow the systematic exploration of algorithmic processes.

All in all, this paper aims to appeal to both the social scientists who want to reform the field of policy process studies and the computational scientists attracted to the examination of social phenomena. Similar to developments in conflict studies, this paper combines theories of policy processes with recent advances in computational modeling and thus couples two fields that could contribute to a better understanding of collective action.

Data Availability

No data were used for this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest with this study.

Acknowledgments

M.S. and I.M. wrote the paper. M.S. reviewed the literature on complexity and policy processes. M.S. and I.M. developed the baseline policy process model. I.M. implemented the model and analyzed the results. I.K. implemented an earlier version of a baseline model of policy processes. K.S., I.K., J.F., and G.D.M.S. provided conceptual and technical comments on the paper. The authors thank Jacob Arbeid, Karsten Donnay, and Chiara Gerosa for additional comments and edits, as well as Didier Wernli and the reviewers for their useful suggestions. I. K. acknowledges support from the ERC Horizon 2020 Research and Innovation Programme under grant 725594 (time-data).

Supplementary Materials

Supplementary material A provides more details on the baseline model of policy processes. Supplementary material B provides an introduction to computational modeling to understand policy processes. In supplementary material A, Figure 1 provides the results of the sensitivity analysis of the model. And, in supplementary material B, Figure 2 provides an overview of a process to develop computational models to study policy processes. (*Supplementary Materials*)

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