Supplementary material

A Computational Turn in Policy Process Studies: Co-evolving Network Dynamics of Policy Change

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Supplementary information

A. A baseline model of policy processes

A.1. Formalization of model

The following describes the algorithmic implementation of our model as well as specifications for the parameters. We implemented the model in python using the mesa package.

Algorithm 1 PolicyModel

```
procedure PROGRESS MODEL
    network ← previous step
    opinion, capability, strategy ← previous step or initialization
    hyper-parameters ← from initialization (see below)
    order ← new random activation order for all agents
    for i in order do
        PolicyAgent(i)
    compute political capital (PC)
    collect all agent data;
    time ← +1
```

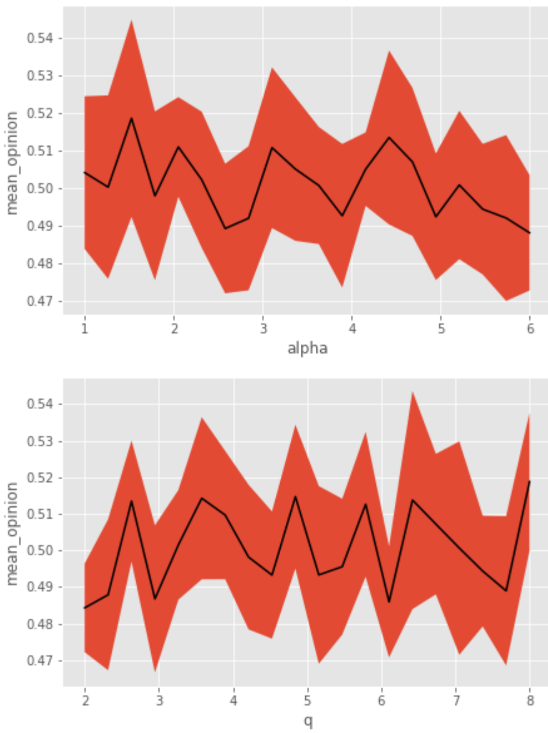
Algorithm 2 PolicyAgent

```
procedure PROGRESS AGENT
    if activation-rate modulo time then
        if success(PC) then
            weighted random choice between strategy (1,2,3)
            if strategy 1 then
                replicator equation (PC = fitness function) updating opinion with random neighbor
            if strategy 2 then
                Maximize support-function by new edge with i ∈ n^(2) more/less opinion distance.
            if strategy 3 then
                Maximize centrality by connecting to i ∈ n^(2) with P(PC_i).
        if number of connections ¿ capability*Dunbar then
            delete random edge
```

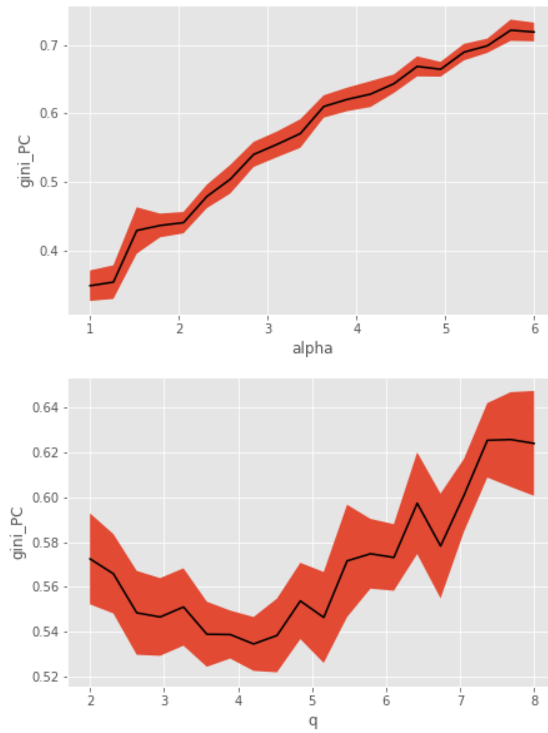
All computations were done with $N = 150$ agents. The activation frequencies of each agent were drawn from a discrete Poisson distribution with expected value of 3. The strategy distribution for each agent is uniformly distributed, while capability follow a truncated normal distribution in the interval $[0.1, 1]$, mean of 0.5 and standard deviation of 0.1. The convergence parameter of the bounded confidence sub-model was set to 0.1. This leaves the two function $\beta(x) = \mathcal{B}(p = 2, q = 3)(x)$ and $\gamma(x) = \alpha \cdot e^{-\alpha x}$ with $\alpha = 3$ as described earlier. Weighted random choices were computed for example by calculating the proportion of agent i PC w.r.t. the total PC summed over all neighboring agents.

A.2. Sensitivity Analysis

Here we show an example of the insights that a sensitivity analysis can provide for the understanding of the baseline model. We only elaborate on the free parameters in the "fitness-function" (PC) here. We vary the parameters $\alpha = \lambda$ of the exponential distribution and the parameter q in the beta-distribution. As we can see in figure 1a, the mean opinion does not exhibit clear effects for any variation of these parameters. However, we do observe that large differences in distribution of accumulated political capital (see Figure 1b). This indicates a certain robustness of the system opinion forming with respect to the distribution of influence.



(a) Effects of varying $\lambda = \alpha$ and q on mean opinion of entire population.



(b) Effects of varying α and q on Gini-coefficient of cumulative PC

Figure 1: Sensitivity analysis

B. Computational models to understand policy processes

The advent of computers was essential for the study of complex systems. They enable the formal and algorithmic study of systems in a way that can be anchored in and validated by empirical data. Computers are a powerful tool to study systems whose behaviors are too complex for human intuition to grasp and cannot be reduced to linear relationships. Computational methods include any computational tool that serves to collect and model data as well as model systems (Lazer et al., 2020).In this section, we briefly discuss current methodological frontiers in policy process studies, present what computational models are and why they are useful, before outlining a process of evidence-driven computational modeling for policy processes. We conclude with a case-study of opinion dynamics.

B.1. Methodological frontiers in examining complexity in policy process studies

While applying complexity theory – even if implicitly – to understand policy processes is increasingly accepted, commonly employed methods fall short of providing systemic explanations that are in line with complexity science. Here, we present the main methodological approaches used in the current policy process literature, discuss their limitations, and outline recent methodological progress that suggests a promising but rocky path for a computational turn of policy process studies.

The works that explicitly use complexity theory to describe policy processes are primarily theoretical. They focus on refuting or validating the use of complexity theory in policy process studies and make recommendations for future research, such as the unification of theories, moving away from simplistic approaches, or recognizing unpredictability (Geyer & Cairney, 2015). In contrast, studies that discuss theories are purely theoretical, qualitative, or quantitative.

The different theories are subject to debate. Scholars unpack criticisms and refine theoretical mechanisms, often based on empirical insights and following events that shed light on policy processes (e.g., 2008 economic crisis, Fukushima's tsunami, or Brexit (Giger & Klüver, 2012)).

When used as lenses to understand specific cases, those theories are usually accompanied by qualitative methods, ranging from ethnographic research to interviews and social network analyses (Keman & Woldendorp, 2016). Those approaches often remedy the lack of granular data on the micro-level dynamics of policy processes. Therefore, scholars need to conduct (semi)structured interviews with policy actors to access information about beliefs, behaviors, network structures, and power dynamics. These research results are often used for thematic analyses or critical analyses that deconstruct social realities (Levy, 2007).

Scholars also employ quantitative methods to validate or refute theories. Surveys, Open Government Data, media data, or the Comparative Agendas Project (Baumgartner, Breunig, & Grossman, 2019) provide sources of micro-level and macro-level data on policy processes. These sources allow the examination of the micro-macro relationships in a quantitative manner. The methods employed are descriptive statistics or statistical models such as linear regressions (Curini & Franzese, 2020).

The current theoretical, qualitative, or quantitative methods constrain the potential of policy process studies unless complemented. First, the literature that applies complexity theory to policy processes primarily focuses on the meaning of complexity as a concept applied to policymaking. It is about building a narrative and a set of mental models to understand complex policymaking systems. While we think building this narrative is essential to change paradigms in social science, it often falls short of identifying empirical facts and laws of policymaking systems (Pollitt, 2009).

Second, building a complexity-infused narrative of policy processes also opens the door to relativism. When associated with concepts from chaos theory, this narrative attracts proponents of postmodernism, interpretivism, and more (Morçöl, 2001). While these critical schools of thought have led to important reflections about the social sciences and the role of the limitations and power of researchers in attempting to understand social phenomena, they tend to suggest that knowledge exists only if highly nuanced (Healy, 2017). This assumption, often implicit, has fostered doubts about the value of abstraction, formalization, quantitative and computational methods (Drucker, 2016), which has slowed down the adoption of computational methods in policy process studies.

Third, from a methodological point of view, policy process studies are divided into roughly two clusters of scholars. On the one hand, scholars push very reductionist approaches and focus on, for instance, linear relationships between micro-level and macro-level data through black-box statistical models (Workman, Jones, & Jochim, 2009). On the other hand, scholars embrace all-encompassing approaches and resort to long essays or textbooks to describe complexity (Geyer & Rihani, 2010). These two groups seem to position themselves differently concerning modeling social phenomena. The first group focuses on models that do not account for the characteristics of complex systems, while the second group does not seem to engage with any form of formal modeling. A computational turn is a way to reconcile these clusters by putting together scientists who formalize policymaking systems and others who have developed detailed theories. By facilitating this turn, we want to motivate the search for more complex but humble models that do not try to hide their assumptions and simplifications but try to test specific theoretical propositions as best as possible.

However, it is important to highlight relevant quantitative advances in policy process studies. First, statistical analyses applied to punctuated equilibrium theory using leptokurtic distributions have been widely tested and demonstrated empirical regularities across countries (Chan & Zhao, 2016; Sebok & Berki, 2018; Sharp, 2019). They notably show a power-law distribution of changes in public budgets. These robust findings are one of the first results that look like the ones complexity science has generated for other systems: macro-level patterns found across systems, which suggest that systems behave the same way and thus lead to the formulation of hypotheses for micro-level dynamics. Scholars have found similar findings in conflict dynamics, where the frequency and severity of conflict also follow a robust power law (Clauset, 2018; Richardson, 1960).

The second advancement – described in the main text – refers to developing network or agent-based models to formalize the micro-level dynamics of policy processes and generate macro-level phenomena (references 27-41 in Table **??**, and especially 37-41 for models that are in line with theories of policy processes). The next sections explain in more detail what computational models are and how to develop them.

B.2. What are computational models?

Before the advent of personal computers in the 1990s, the formalization of social systems fell short of replicating complex dynamics. They were able to generate either deterministic dynamics (Richardson, 1960) or chaotic dynamics (Saperstein, 1984). Later on in the 1990s, networks of computers could facilitate purely theoretical computational research in e.g. international relations and the validation or refutation of traditional theories (Duffy, 1992). As of the 2000s, computational models became more precise and increasingly empirically validated (Clauset & Gleditsch, 2012; Weidmann & Salehyan, 2013). In sixty years, the field of social system formalization moved from systems of equations to computational toy models and on to empirically-validated computational models. It is this latter, empirically-validated computational type we want to encourage in policy process studies.

Computational models can be referred to as dynamic formalism because they combine two core components. First, models are implemented as systems of equations, computer code or a mix of both (Thurner, Hanel, & Klimek, 2018). This process of formalization aims to reduce the description of system parts and mechanisms to a minimum of components in a way that is theoretically and/or empirically valid. To model complex systems, formalizations often include update rules or feedback loops, which are iterative mechanisms that lead to adaptation, absorption or amplification. Second, computational power is used to run the formalization and activate models' iterative processes. The iterations then generate system dynamics.

To examine social systems, a prominent class of computational models are agent-based models (Page, 2008). These models formalize the characteristics and adaptive behaviors of agents (e.g. policy actors), their mode of interactions and network structures (e.g. topology of policy networks) and the macro-level properties (coalitions, attention dynamics, collective decisions, ...) that result from iterative processes of agent-level adaptation (e.g. opinion changes, decisions, etc.). Agent-based models are increasingly popular in political science, especially in the study of intra-state armed conflict (Neumann & Lorenz, 2019).

"Is it possible to model human behavior?" is a question that is repeatedly raised in political science departments and conferences. This paper builds on the insight that, in fact, all descriptions of human behavior are models. Verbal descriptions may seem more faithful because of their fuzziness and room for interpretation, allowing people to project their own models on what is meant. Yet, current verbal descriptions of policy processes based on complexity theory are difficult to test empirically because they are often too general. Therefore, a minimum level of formalization is needed. Similarly, mathematical models without implementation fall short of eliciting complex dynamics. It is the coupling of mathematical formalization and computational power that can usefully model human behavior and explain social dynamics (Helbing et al., 2015). In short, all models are wrong, some models are useful (Box, 1976). Any modeling effort needs to state its limitations clearly, but models do not need to be perfect. They need to fit the theory and the data and be tested against reality.

B.3. The value of computational models

Computational models are particularly useful because they formalize and generate dynamics of iterative, stateful, path-dependent processes. This is important because social systems feature plenty of iterative processes. Armed conflicts, opinion dynamics or economic supply and demand relationships, for example, are all iterative processes that boil down to how agents update as a function of the behavior of other agents. Modeling such iterative processes enabled the study of emergent cooperation among heterogeneous agents, for instance (Axelrod, 1997).

Computational models also enable the study of the dynamics of systems of equations that are not analytically solvable. Differential equations of complex systems rapidly become too complex to be solved by hand and most are non-deterministic (Thurner et al., 2018). Therefore, implementing those equations as computational models enables researchers to generate dynamics and then analyze them statistically. Relatedly, while it is extremely difficult to make point-predictions about complex systems, computational models can make accurate predictions of outcome distributions by running thousands of simulations (Lazer et al., 2020; Thurner et al., 2018).

Computational models enable to generate data on either micro-level or macro-level dynamics when no real data is available (Epstein, 2012). Therefore, models may be built on theory and then used to generate data with which statistical analyses are possible. This is particularly useful to examine complex systems for which data collection is very difficult (secret processes, or dangerous locations) and to analyze counterfactuals in possible future outcomes, assuming the model has been sufficiently validated (Page, 2018).

Computational models also allow researchers to reconcile the study of micro-level and macro-level dynamics. As the mainstream literature tends to dissociate both (e.g. micro- versus macroeconomics, or policy analysis versus behavioral public policy), the use of computational models can link macro level dynamics to the behavior of their constituent parts. They directly integrate the concept of emergence and can produce the nonlinear dynamics associated with emergent phenomena.

In social systems, there is often one history that cannot be repeated, which prevents the rigorous understanding of what-if scenarios. Computational models allow researchers to repeat artificial scenarios and compare them to each other as statistical equivalents (Thurner et al., 2018). The explicitness and transparency of computational modeling also allow to design models and interpret results in a participatory manner (Bommel et al., 2014).

It is, however, very challenging to reliably attain the added-value we proposed. The next section presents a guide to maximize the success of computational modeling efforts.

B.4. From model conceptualization to the identification of signatures in policy processes

Recent literature on computational social science has aggregated pieces of advice for creating valuable models. Bhavnani and colleagues (2020) summarize this advice in a process to develop robust evidence-driven computational models. We adapt their method to policy process studies. The advantage of this method is that it places computational modeling within a larger scientific process, thus linking different stages of research design.

Figure 2 illustrates the resulting five step process: (1) model conceptualization; (2) model implementation; (3) data construction; (4) model validation and refinement; and (5) counterfactual analysis. As such, it guides researchers in the identification of the signatures of complex policymaking systems. While the figure depicts a linear process, it is inherently iterative. In the rest of this section, we describe each step and link it to the policy process literature.

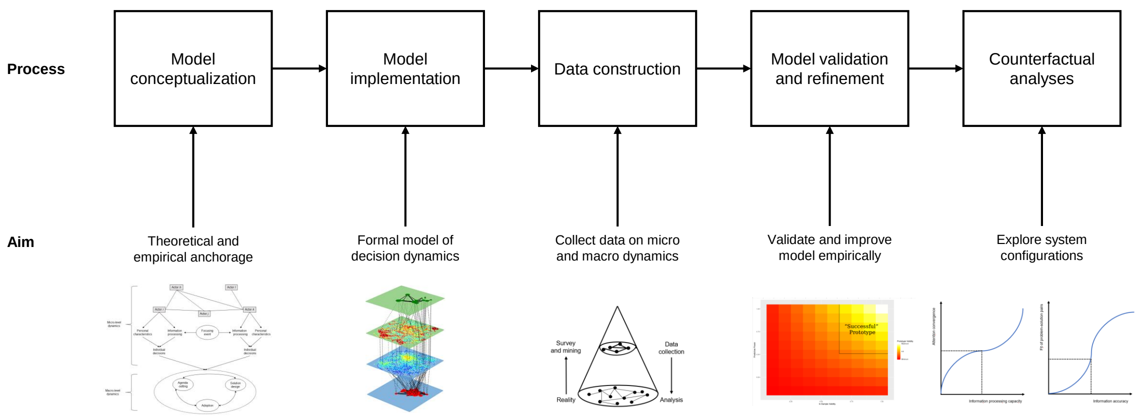


Figure 2: A process for computational modeling in policy process studies (adapted from Bhavnani et al. (2020))

Model conceptualization: the first step of computational modeling is the definition of parts, mechanisms and outcomes. Model conceptualization is, in a way, a synthesis of many different information sources. To conceptualize a model of policymaking, it is possible to draw from existing theories of policy processes (Weible & Sabatier, 2018), existing case-studies, expert opinion, interviews and surveys. Altogether, these sources of information enable the specification of system parts, the selection of specific mechanisms and link micro-level with macro-level dynamics. A crude, conceptual model of policymaking, for instance, can be deduced from punctuated equilibrium theory as shown in Box 1.

Box 1. A simple verbal model of policy processes based on punctuated equilibrium theory

Policy actors have two adaptive characteristics which is their current attention and opinion, they interact within a decentralized network structure, and update their attention and opinion as a function of their neighbors' characteristics. Actors pursue two strategies: trying to reach better positions in the network and forming coalitions with value-aligned actors. Iteratively, this process leads to aggregate patterns of attention such as periods of inertia and periods of change, and contagion of opinion (Jones & Baumgartner, 2005a, 2005b).

Model implementation: once the model is conceptualized and matches descriptions and data from available sources of information, one can implement it. Implementation includes formalization of the model as systems of equations and computer code. The formalization specifies the relationship between variables and their associated probabilities, how the model aggregates observables (like patterns of attention), and how it reports results. Formalization often is a crucial step to test the robustness of the conceptual model because it forces researchers to spell out modeling assumptions and will thus challenge fuzzy definitions. Relevant mathematical and software programming tools must be employed and their use justified (see next section). Model implementation also involves many checks to test whether the implementation produces the intended dynamics. Sensitivity analyses are useful to check whether the model behaves in a realistic manner. In policy process studies, the implementation of the conceptual model could draw from differential equations that help formalize co-evolving networks (Thurner et al., 2018).

Data construction: once the model is implemented, it is called a toy model, as its results will not be empirically valid and can only serve exploratory purposes. To produce empirically valid results, the third step is to identify, collect and prepare data to seed and validate the model (see next paragraph). Data is required to specify the initial conditions of the model, such as the number of policy actors, their initial focus, the network topology and the frequency and size of exogenous signals, such as media coverage. To validate the simulated results - such as aggregate patterns of attention, the rate of new decisions, and the evolution of network topologies - more data is required.

Finding useful data is a challenge. Data on micro-level processes is scarce and often qualitative. There is some progress in collecting such data under the label 'big data' by relying on email data to identify network topology and social media data to identify attention patterns and political behavior (Donnay, 2017). Surveys and behavioral experiments can also provide complementary information, especially on behavioral profiles (Moser & Kalton, 2017). Data on macro-level processes, such as agendas, attention or decisions, is easier to find in a quantitative format. The Comparative Agendas Project centralizes data on public budgets (Baumgartner et al., 2019) and the Open Government Data group reports decisions and bills issued by national governments (Ubaldi, 2013). In most cases, the identified data will not be directly usable to seed and validate the model. It will require "construction" of datasets that can be imported into the model by, for instance, matching dataset variables with model parameters. Or by drawing probability distributions from datasets to define update rules, frequency of exogenous signals, etc.

Model validation and refinement: once data is prepared, researchers can use it to seed a model's initial conditions and validate simulated outcomes. Multiple methods can be used to measure the fit of simulated results with empirical data, including the root-mean-square-deviation, but also precision, recall and F1 scores. F1 scores are particularly useful as they provide information on how many observations the model gets right or wrong, instead of a simple overall correlation or deviation (Goutte & Gaussier, 2005). Data can be used to test internal validity (using in-sample data from a specific case) and then external validity (using out-of-sample data from other cases). Here again, the insights from punctuated equilibrium theory are useful. The power-law of public budgets has been empirically validated across contexts. It would be interesting to build a model of the micro-level dynamics that lead to its emergence and then explore whether its mechanisms are valid in various contexts.

Counterfactual analysis: once models are empirically validated, at least internally, it is possible to use them as artificial laboratories to explore their signatures. Conducting counterfactual analyses allows to understand how the system behaves when different initial conditions are chosen. For instance, one can explore different levels of network centrality, different attention probability updates, different frequencies and sizes of exogenous signals, and explore how the system behaves as a function of those changes. In complexity science, it is essential to explore critical points - the equivalent of the 99 to 100 degree shift in water temperature that leads to a phase transition. For instance, does increasing network density from one specific value to the next lead to radical changes at the macro-level? Those analyses could allow the robust identification of the drivers of policymaking. As such, they can then be used to generate recommendations on how to design policy processes.

This five-step process allows researchers to move from the conceptual models, often described in policy process studies, to the exploration of common signatures of complex policymaking systems. It is important to iterate on these five steps, instead of trying to perfect each of them only once. The questions in the following two sections relate to modeling particular phenomena in policy process studies and avenues to be explored with this process.

Applying this five-step process to policy process studies highlight at least five areas of progress. First, it is important to carefully select which concept of policy process studies deserve formalization and then identify promising tools. Second, once the approach provides isolated formal components of policy processes, one can select and assemble them to design models. Models will be used to elicit dynamics that can be validated theoretically. The idea is to check whether results come close to the expectations in the literature. Third, more effort must be put into collecting data on the characteristics, behavior and network connection of policy actors. Building datasets of micro-level determinants is crucial to advance empirical research and examine how micro-level dynamics lead to macro-level outcomes. Fourth, models can be expanded and seeded and validated with empirical data. Fifth, empirically-validated models can then be used to explore counterfactual scenarios and identify critical points of policymaking systems. These five steps can apply to single projects but also to the entire field of computational policy process studies. As computational projects multiply, they can feed into each other and contribute to a better understanding of how to model policy processes, increased data validity, and the identification of key critical points.

B.5. A case study in opinion dynamics

Using the above five-step process, we illustrate the crucial step that policy process studies should take more often – model formalization. We retrace what makes for a successful formal model of social dynamics. We aim to highlight advantages and challenges on the path to attain a causal model and with it a mechanistic explanation of policy processes. It is in principle hard to make a precise verbal explanation such that it uniquely defines a system in its micro- and macro-states. Or even to prove a causal relationship between them. The immediate payoff of any formal model of the policy process is a proof-of-concept for the internal consistency of stated axioms, enabling us to explore scenarios and generate hypotheses. A prominent example being Axelrod's computer tournaments to find optimal strategies for the iterated prisoner's dilemma (Axelrod & Hamilton, 1981). After finding the winning strategy ("tit-for-tat"), Axelrod et al. could provide an explanation of why such behavior is common in any species with similar selection pressure. However, the process of policymaking constitutes an open system, meaning that it is highly interconnected on many different levels of abstraction with some larger system, outside the scope of any modeling attempt. Consequently, models of such systems will most likely be unsuitable for forecasting and restricted to improving the qualitative understanding of each constituent's contribution to the overall dynamics.

For example, R. Hegselman and U. Krause followed these considerations when developing their model of opinion dynamics (Hegselmann, Krause, et al., 2002). The goal of their model was specified as providing mechanistic explanations for the process of opinion fragmentation. What are the conditions for consensus or polarization to emerge? The first step was to formulate axiomatic rules that they believed to be the essential rules of the process. The second step was to define a corresponding formal mathematical framework that, besides allowing for further extensions, most importantly answered the following question: To what extent do the system dynamics follow from stated assumptions? In what follows, we retrace their approach and formalization and, thus, illustrate the process of formalizing social phenomena:

With n as the number of agents contained in the considered population, some discrete-time $T = 1, 2, ...$ and some continuous opinion dynamics model are defined. We then want to define the most basic updating mechanism for each actor, namely taking the average over the opinion of neighboring agents and the agent's own opinion. However, actors do not weigh everyone's opinion equally. Therefore we define weights for all connections in the undirected network, resulting in the adjacency matrix $A := (a_{ij})$ for the network. As such, the updating mechanism can be compactly written as:

$$\mathbf{x}(t+1) = \mathbf{A}(t, \mathbf{x}(t)) \cdot \mathbf{x}(t) \quad \text{for} \quad t \in T$$

We are now able to translate the initial more general research question into a more formal language: How does a given initial opinion profile of the entire network influence the final opinion distribution? Equipped with this formalization we can now investigate the most basic case with $\mathbf{A}$ as a stochastic matrix. This allows estimating convergence time to the steady-state depending on the structure of $\mathbf{A}$. We identify the network structure and opinion updating rule of each actor as the key elements that dictate the dynamics. Hence, making them the focus of further analytical and empirical analysis (Hegselmann et al., 2002).

Building on this minimal model, Hegselman and Krause introduced many interesting extensions, such as the property of susceptibility for each actor or "hardening of positions" where actors weigh their own opinion more strongly over time. Moreover, they analyzed non-linear extensions, which were introduced by defining conditions under which weights can become zero - meaning actors are ignoring each other. One possible implementation is to define a confidence level ϵ_i to each agent similar to the Deffuant-Weisbuch model (Deffuant, Neau, Amblard, & Weisbuch, 2000). Such models are called bounded confidence models, where the confidence level acts as a threshold parameter that defines the level of discrepancy of opinions beyond which actors ignore each other. Further research investigated the implications of asymmetric confidence intervals between the agents and of the underlying network structure. From this we learn that choosing the right level of abstraction (i.e. minimal model) is essential and allows for useful extensions at a later point. Ideally, we do not arrive at a single, large and specific self-consistent model, but rather at a cluster of different models exploring implications of different assumptions.

References

Axelrod, R. (1997). *The complexity of cooperation: Agent-based models of competition and collaboration* (Vol. 3). Princeton University Press.

Axelrod, R., & Hamilton, W. D. (1981). The Evolution of Cooperation. *Science*, *211*(4489), 1390–1396. doi: 10.1126/science.7466396

Baumgartner, F. R., Breunig, C., & Grossman, E. (2019). *Comparative Policy Agendas: Theory, Tools, Data.* Oxford University Press.

Bhavnani, R., Donnay, K., & Reul, M. (2020). Evidence-driven computational modeling. *The SAGE Handbook of Research Methods in Political Science and International Relations*.

Bommel, P., Dieguez, F., Bartaburu, D., Duarte, E., Montes, E., Pereira Machín, M., ... Morales Grosskopf, H. (2014). A Further Step Towards Participatory Modelling. Fostering Stakeholder Involvement in Designing Models by Using Executable UML. *Journal of Artificial Societies and Social Simulation*, *17*(1), 6.

Box, G. E. (1976). Science and statistics. *Journal of the American Statistical Association*, *71*(356), 791–799.

Chan, K. N., & Zhao, S. (2016). Punctuated Equilibrium and the Information Disadvantage of Authoritarianism: Evidence from the People's Republic of China. *Policy Studies Journal*, *44*(2), 134–155. doi: 10.1111/psj.12138

Clauset, A. (2018). Trends and fluctuations in the severity of interstate wars. *Science Advances*, *4*(2), eaao3580. doi: 10.1126/sciadv.aao3580

Clauset, A., & Gleditsch, K. S. (2012). The developmental dynamics of terrorist organizations. *PloS one*, *7*(11), e48633.

Curini, L., & Franzese, R. (2020). *The SAGE Handbook of Research Methods in Political Science and International Relations.* SAGE.

Deffuant, G., Neau, D., Amblard, F., & Weisbuch, G. (2000). Mixing beliefs among interacting agents. *Advances in Complex Systems*, *03*(01n04), 87–98. doi: 10.1142/S0219525900000078

Donnay, K. (2017). Big Data for Monitoring Political Instability. *International Development Policy — Revue internationale de politique de développement*, *8*(1). doi: 10.4000/poldev.2468

Drucker, J. (2016). At the intersection of computational methods and the traditional humanities. *Digital Humanities and Digital Media*, 43–68. doi: 10.25969/mediarep/11912

Duffy, G. (1992). Concurrent interstate conflict simulations: Testing the effects of the serial assumption. *Mathematical and Computer Modelling*, *16*(8-9), 241–270.

Epstein, J. M. (2012). *Generative social science.* Princeton University Press.

Geyer, R., & Cairney, P. (2015). *Handbook on complexity and public policy.* Edward Elgar Publishing.

Geyer, R., & Rihani, S. (2010). Complexity and Public Policy: A New Approach to Twenty-First Century Politics. *Policy and Society. Routledge*.

Giger, N., & Klüver, H. (2012). Focusing events and policy change: The aftermath of Fukushima. In *Proceedings of the European Political Science Association Conference, Berlin, Germany* (pp. 21–23).

Goutte, C., & Gaussier, E. (2005). A Probabilistic Interpretation of Precision, Recall and F-Score, with Implication for Evaluation. In D. E. Losada & J. M. Fernández-Luna (Eds.), *Advances in Information Retrieval* (pp. 345–359). Berlin, Heidelberg: Springer. doi: 10.1007/978-3-540-31865-1_25

Healy, K. (2017). Fuck Nuance. *Sociological Theory*, *35*(2), 118–127. doi: 10.1177/0735275117709046

Hegselmann, R., Krause, U., et al. (2002). Opinion dynamics and bounded confidence models, analysis, and simulation. *Journal of artificial societies and social simulation*, *5*(3).

Helbing, D., Brockmann, D., Chadefaux, T., Donnay, K., Blanke, U., Woolley-Meza, O., ... others (2015). Saving human lives: What complexity science and information systems can contribute. *Journal of statistical physics*, *158*(3), 735–781.

Jones, B. D., & Baumgartner, F. R. (2005a). A Model of Choice for Public Policy. *Journal of Public Administration Research and Theory*, *15*(3), 325–351. doi: 10.1093/jopart/mui018

Jones, B. D., & Baumgartner, F. R. (2005b). *The Politics of Attention: How Government Prioritizes*

Problems. University of Chicago Press.
Keman, H., & Woldendorp, J. J. (2016). *Handbook of Research Methods and Applications in Political Science*. Edward Elgar Publishing.
Lazer, D. M. J., Pentland, A., Watts, D. J., Aral, S., Athey, S., Contractor, N., ... Wagner, C. (2020). Computational social science: Obstacles and opportunities. *Science*, *369*(6507), 1060–1062. doi: 10.1126/science.aaz8170
Levy, J. S. (2007). Qualitative Methods and Cross-Method Dialogue in Political Science. *Comparative Political Studies*, *40*(2), 196–214. doi: 10.1177/0010414006296348
Morçöl, G. (2001). What Is Complexity Science? Postmodernist or Postpositivist? *Emergence*, *3*(1), 104–119. doi: 10.1207/S15327000EM0301_07
Moser, C. A., & Kalton, G. (2017). *Survey Methods in Social Investigation*. Routledge.
Neumann, M., & Lorenz, J. (2019). Agentenbasierte Simulation in der Politikwissenschaft. In C. Wagemann, A. Goerres, & M. Siewert (Eds.), *Handbuch Methoden der Politikwissenschaft* (pp. 1–24). Wiesbaden: Springer Fachmedien. doi: 10.1007/978-3-658-16937-4_34-1
Page, S. E. (2008). Agent-based models. *The New Palgrave Dictionary of Economics: Volume 1–8*, 47–52.
Page, S. E. (2018). *The model thinker: What you need to know to make data work for you*. Hachette UK.
Pollitt, C. (2009). Complexity Theory and Evolutionary Public Administration: A Sceptical Afterword. In *Managing Complex Governance Systems*. Routledge.
Richardson, L. F. (1960). *Arms and insecurity: A mathematical study of the causes and origins of war*. Boxwood Press.
Saperstein, A. M. (1984). Chaos—a model for the outbreak of war. *Nature*, *309*(5966), 303–305.
Sebok, M., & Berki, T. (2018). Punctuated equilibrium in democracy and autocracy: An analysis of Hungarian budgeting between 1868 and 2013. *European Political Science Review*, *10*(4). doi: 10.1017/S1755773918000115
Sharp, T. (2019). Wars, presidents, and punctuated equilibriums in US defense spending. *Policy Sciences*, 1–30.
Thurner, S., Hanel, R., & Klimek, P. (2018). *Introduction to the theory of complex systems*. Oxford University Press.
Ubaldi, B. (2013). *Open Government Data: Towards Empirical Analysis of Open Government Data Initiatives* (Tech. Rep.). Paris: OECD. doi: 10.1787/5k46bj4f03s7-en
Weible, C. M., & Sabatier, P. A. (2018). *Theories of the Policy Process*. Routledge.
Weidmann, N. B., & Salehyan, I. (2013). Violence and ethnic segregation: A computational model applied to Baghdad. *International Studies Quarterly*, *57*(1), 52–64.
Workman, S., Jones, B. D., & Jochim, A. E. (2009). Information Processing and Policy Dynamics. *Policy Studies Journal*, *37*(1), 75–92. doi: 10.1111/j.1541-0072.2008.00296.x