The importance of a dynamic network within a model of politics

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Abstract. Many simulation models of social influence are for the theoretical exploration of the outcomes resulting from certain mechanisms. Thus they tend to be relative focused on one mechanism at a time – The KISS approach. Here we take a more KIDS approach, looking at the interaction of two mechanisms within an evidence-led simulation of political behaviour (Austria 2013-2017). In this simulation there is not only the mutual social influence of attitudes (within a 7D space), but this social influence is constrained by a social network. However, one can also allow this social network to adapt based on the interactions between agents, so the social attitudes and social networks co-evolve. In this model, we find that (a) whether the social network is allowed to adapt is more important to the outcomes than the particular kind of social network it is initialized with, but also that (b) (given all the other mechanisms, parameters and structures in this model) a changing social network seems essential to getting outcomes that are qualitatively similar to the patterns in the observed polling data.

Keywords: Agent-based simulation, Opinion dynamics, Social influence, social network.

1 Introduction

There are now a lot of models that incorporate some kind of opinion dynamics, many of them following # Deffuant2000. For a structured survey of such models, see #flache2017. However, most of these models are intended for the abstract exploration of the consequences of their mechanisms, which is easier if the model is kept relatively simple (certainly free of those details considered not essential to this task). In such models homophily basically determines who will actually influence whom – although any two agents can interact, they only influence each other if their opinions are sufficiently close (the difference less than their individual uncertainty). However, when trying to understand social influence in observed cases this assumption is not plausible – people only try interacting with a restricted range of people, namely those in their extended social networks (those they interact with face-face, on the phone, on facebook etc.). In such cases a social network constrains social influence in addition to homophily as in (??there must be examples of this to cite??). This changes the structure of influence, for example a person with opinions that are very different from most others is unlikely to repeatedly contact random others in the hope of finding someone with similar views to their own – more plausibly, they will adapt their social network so that their interactions will be more fruitful more of the time.

In this paper, we look at the importance of the social network on the social influence process within a simulation of political behaviour, specifically some of the politics in Austria between 2013 and 2017. Unlike those models which are aimed at exploring the consequences of abstract mechanisms, this model aimed to be led by the available evidence and data (following the 'KIDS' approach #EdmondsMoss2005). This results in a much more complicated model. Here, we are interested in the following questions:

1. How does the social network change how social influence works within this model?
2. What social network elements seems to be necessary to get anything like the observed polling outcomes?

2 A Model of Voting and Party Competition in Austria

The model used for the exploration of different social influence mechanisms is an agent-based model of voting and party competition in Austria [#meyer_2022]. It simulates the development in Austrian party politics between the national elections of 2013 and 2017, a period that was affected by the refugee crisis of 2015/2016, the ensuing rise of the populist FPÖ, and the leadership-change in and shift to the right by the conservative ÖVP. Parties and voters are agents interacting within a political space spanned by seven policy issues ranging from economical, societal, and environmental topics to immigration policy. Each of these is interpreted as a spatial dimension within a left-right ideological spectrum. Parties and voters take positions on particular issues with lower values indicating they are ideologically left-leaning and higher values indicating they are ideologically right-leaning. The respective values for each voter and party agent are initialised from empirical data: the 2013 Austrian National Election Study (AUTNES) [#Kritzinger et al. 2013] for the voters and the Chapel Hill Expert Survey administered in 2014 [#Polk et al. 2017] for the parties.

Other agent attributes are also defined by the data. For the voters these are demographic characteristics (age, gender, level of education, residential area, income situation), political attitudes (closest party, level of political interest, propensities to vote for any of the parties, probability to vote in the election) and up to three issues of the political space they find most important. For the parties these are their names (included are the seven major Austrian political parties at the time, namely SPÖ, ÖVP, FPÖ, Grüne, NEOS, BZÖ, and Team Stronach) and equally up to three issues identified as most important. Both parties and voters assign weights to them according to their importance.

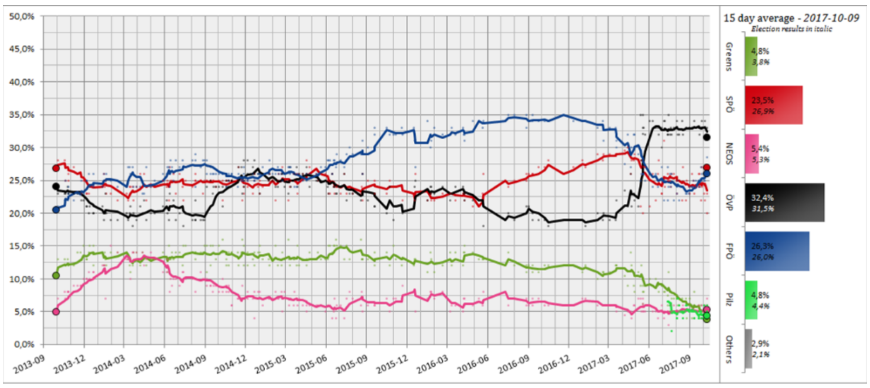
Empirical data on issue salience in the public opinion available from the Eurobarometer series of surveys [#ref] is used as a proxy to model the influence of the media. After matching the relevant Eurobarometer categories to the seven issues represented in the model and rescaling the data, the respective values are applied as probabilities to select the topic to talk about during voter interactions to emulate the media's influence on voter opinion.

The behaviour of voter and party agents is based on theories from the political science literature. To attract voters, parties apply one of a variety of strategies to position themselves in the political landscape [#Laver 2005, #Muis and Scholte 2013]; they can choose from “Sticker” (stick to their ideological positions), “Aggregator” (move towards the centre of supporters), “Satisficer” (move like an aggregator until the aspired vote-share is reached), or “Hunter” (seek votes opportunistically by changing direction whenever the vote-share drops) . The movement of both “Hunter” and “Aggregator” are restrained to a party’s most important issues.

Voters use another set of decision-making strategies to decide which party to vote for. The five strategies identified by (Lau et al. 2018) comprise “Rational choice”, which chooses the party closest in all seven dimensions; “Confirmatory”, which picks the party a voter feels closest to (taken from AUTNES); “Fast and frugal”, which only looks at the two most important issues to determine the closest party; “Heuristic-based”, in which a voter follows recommendations from friends; and “Go-with-your-gut”, where voters follow their instinct.

Voters can change their opinions on any of the policy issues due to social influence. This is realized as a bounded confidence opinion dynamics approach, in which randomly paired voter agents only interact if their ideological distance falls under a certain threshold. This threshold represents a voter’s ‘affective level’ and is different for each agent [#schweighofer]. As the outcome of an interaction voters either move closer together on the discussed topic (agreement) or further apart (disagreement) [#baldassarri].

The best results obtained with this model using an empirically determined mix of voter decision strategies qualitatively matched the target data, which are the observed opinion polls from 2013 to 2017 (see **Fig. 1**). However, only a small number of runs did this.



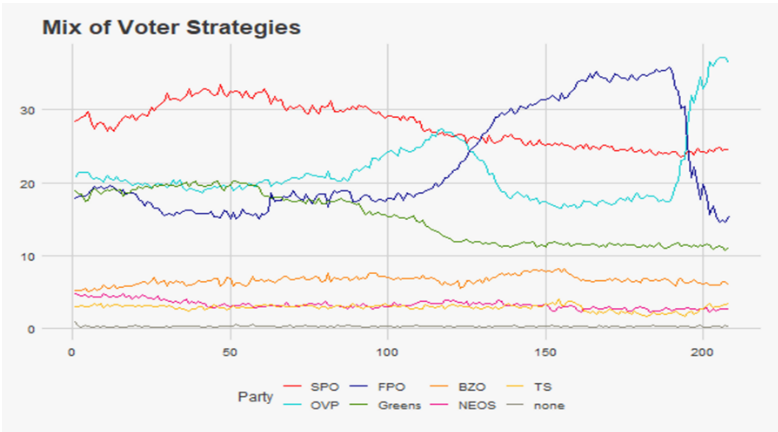


Fig. 1. Observed polling data for the period 2013-2017 [#source] vs. model-generated polling data.

3 Social Influence Mechanisms

The social influence mechanism implemented in the Austria model is an opinion dynamics approach which assumes bounded confidence [#deffuant #hegselmann&Krause]. Two agents only interact if their opinion on the policy issue chosen for discussion (influenced by the Eurobarometer data) is not too dissimilar, i.e., does not exceed a certain confidence threshold. Similarity of opinion is measured as the Euclidean distance between the two agents' opinion in the political space. Following [#schweighofer], the confidence threshold is interpreted as affective involvement and is therefore different for each agent. The Austria model derives this value from empirical data, in particular the political interest of voters, assuming that higher political interest coincides with stronger involvement.

3.1 Random Mixing (totally connected network)

In the first version, as usual with opinion dynamics models, interaction partners are chosen randomly from the whole population of agents. In social network terms, this can be interpreted as everyone being connected to everyone else. An analysis of the interactions happening during simulation runs with a small number of discussions per time step (parameter *discussion-freq* set to 1) show that any two randomly chosen voter agents talk to each other at most 5-6 times over the course of the simulation (208 time steps). However, this is very rare; most will never interact (>70%) or only once (about 22%). Agents have between about 40 to over 400 different interaction partners – numbers at odds with some evidence from political science research, which suggests that the size of political discussion networks is relatively small: people tend to talk to 0-5 other people about politics [#Lake & Huckfeldt 1998].

3.2 Fixed social networks

To investigate if the realism of the model can be improved by choosing discussion partners from a voter's social links as suggested by political science research, we consider four different network topologies:

- A regular random network, where each voter is connected to exactly n randomly chosen other voters (with n specified by model parameter *number-of-friends*).
- An Erdös-Rényi random network, where each configuration of a network with the given mean degree is equally likely; the algorithm used to create this network keeps adding links between randomly chosen pairs of voters until the mean degree (model parameter *number-of-friends*) is reached.
- A scale-free network obtained from preferential attachment, i.e., the probability to connect with a voter rises with the number of links this voter already has.
- The homophily-based network as already implemented in the model, where each voter forms links with other voters most similar in age, education, and residential area from a pool of randomly chosen individuals.

To achieve networks as close as possible to the specification of political discussion networks with 0-5 discussants for every voter, we set the parameter n to 3. Table 1 shows the resulting typical values for the different topologies and a population of 1060 voters. The chosen social network is created at model initialisation and remains fixed during a simulation run.

Table 1. Social network characteristics

Network type	*Total number of links*	*% voters with 0-5 links*	*Mean degree*	*Max degree*	*Min degree*	*Number of unconnected voters*
Homophily-based	1064	99.3	≈2	7	0	123
Regular random	1590	100	3	3	3	0
Erdös-Rényi	1590	91.3	3	11	0	50
Scale-free	1059	95.5	≈2	58	1	0

3.3 Dynamic social networks

Keeping the network fixed means that interactions outside the existing social links are not possible. Since these links are still mostly assigned randomly, however, some connections may function less well than others. Some linked voters might be ideologically too far apart on one or more issues for them to ever engage in a conversation on that topic, whereas others might interact but disagree repeatedly. The simulated time frame of four years is also long enough for it to be possible that voters could make new acquaintances to have political discussions with.

We therefore consider an alternative scenario with dynamic networks, where agents may form new random links, friend-of-friend links or drop links with those they disagree with a lot. To this end we introduce three new model parameters: the maximum number of disagreements before the link is dropped (*drop-threshold*), the chance to make a new link (*new-link-prob*) and the proportion for new links to be created with friends of a friend (*fof-prop*). The outcome of any interaction between two voters is recorded on the link that connects them and stored in a list (-1 for disagreement, +1 for agreement). At the end of each simulation step, a process to evolve the social network is added. This first deletes all links where the number of disagreements exceeds the drop threshold. Then each voter has the chance to form a new link with either a friend of a friend (80%) or a randomly chosen other voter (20%).

In the experiments reported here, the drop threshold was set to 10 and the probability for a new link to 0.007. While the latter number looks rather small, it avoids an excessive increase in the number of links, keeping the overall 'shape' of the network close to the requirements for political discussion networks.

4 Discussion of Results

4.1 Effect of fixed social networks

Fixed and dynamic networks are explored through a set number of different scenarios, defined by varying a few chosen model parameters. These govern how often political discussions happen amongst voters (*discussion-freq*: 1, 2 or 5), how easily voters are convinced to change their opinion (*voter-adapt-prob*: 0.5 or 1) and the shape (*network-type*: one of the four different topologies homophily-based, regular random, Erdös-Rényi, preferential attachment) and variability of the social network (model parameter *dynamic-network?* switched off or on). Each scenario is simulated 50 times with the same set of random number seeds.

To compare the different scenarios, we look at election results in the form of possible government formation and measure voter satisfaction as distance to the new government in the two most important issues. Government formation here solely takes the vote shares of parties into account. The largest party forms a coalition with the next largest party or parties until they reach a majority (> 50%). The ideological positions of such a government in the political space are then computed as the weighted averages of the coalition partners. While this may result in very unrealistic coalitions, for example combining the populist FPÖ with the Greens, it is still a suitable indication of the outcome of a simulation.

To see if voter interaction via the social network improves the realism of the results, each run is compared to the observed historical data. We find that for the fixed networks, none of the runs come close and that the network topology does not make much of a difference. The SPÖ prevails as the biggest party throughout, while the ÖVP comes out as the second biggest party in about 70% of runs, forming a coalition with the SPÖ. The populist FPÖ manages to join the government in up to a third of the cases, mostly in 3-party coalitions. The change of issue salience in the public opinion (rise of the immigration topic) never leads to a dramatic gain for the FPÖ but rather benefits the ÖVP temporarily (see **Fig. 2** for an example). This effect is slightly more pronounced with increased discussion frequency, coinciding with a decrease in the government participation of the populists. Figure # illustrates the subtle trends with regard to voter interaction.

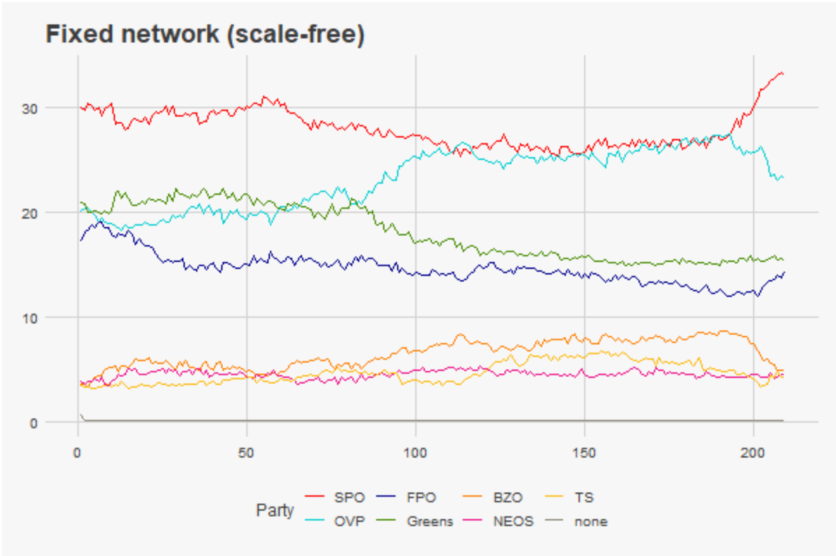


Fig. 2. Typical run with a fixed network (scenario: scale-free network, discussion frequency 2, voter adaptation probability 1)

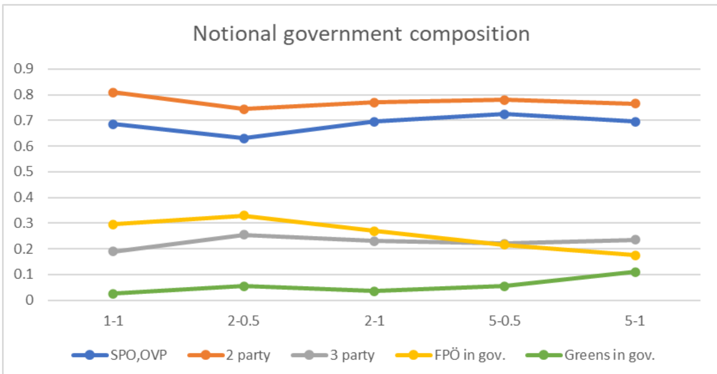


Fig. 3. Composition of notional governments over different scenarios across all fixed networks

The results differ for the dynamic networks, i.e., if voter agents are allowed to gain new discussion partners and stop talking to people they disagree with a lot during a simulation. Regardless of network type, there are no longer any 3-party coalitions, and the Greens are never in government. The larger parties win enough vote share to only need one other coalition partner and the Greens are not amongst those. The SPÖ is still either the biggest or the second biggest party, but the FPÖ now manages to win up to 27% of cases depending on the parameter settings defining the voter interaction (*discussion* *frequency*, *voter-adapt-prob*): starting from 3% (scenarios 1-1, 2-0.5) to 16% (scenario 2-1), to 27% (scenario 5-1). The gain for the ÖVP is even more dramatic, ranging from 3% (scenarios 1-1, 2-0.5) to 43.5% (scenario 5-1). The more people talk and convince each other, the higher the chance that the FPÖ or ÖVP become the largest party instead of the SPÖ (see **Fig. 4**).

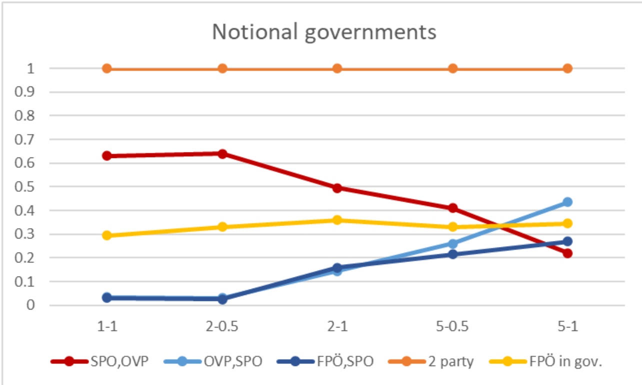


Fig. 4. Composition of notional governments over different scenarios across dynamic networks

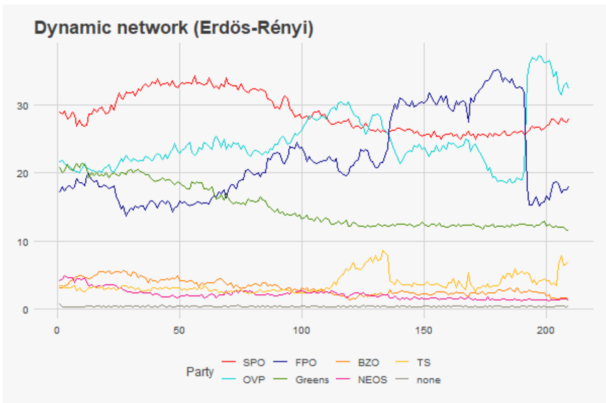


Fig. 5. Best model results with dynamic networks

Change in issue salience in the public opinion now has a noticeable effect, though the advantage is still mostly taken by the ÖVP. A few runs do come qualitatively close to the historical data and here the network type does make a difference: while the Erdös-Rényi and Regular Random network both display examples of "successful" runs the other two network types (homophily-based and scale-free) do not. **Fig. 5** shows the best result, obtained with the Erdös-Renyi network in scenario 5-1 (*discussion-freq* 5, *voter-adapt-prob* 1).

4.2 Sensitivity to different network types and whether they are dynamic

To see the impact of various non-network settings in fixed and dynamic network cases we varied the following parameters with 10 independent runs for each set (192,000 simulation runs in total).

- *discussion-freq*: {1, 2}
- *max-p-move*: {0.5, 1}
- *voter-adapt-prob*: {0.5, 1}
- *max-salience-change*: {1.5, 3}
- *dynamic-network?*: {true, false}
- *network-type*: {"homophily-based political discussion network", "regular random network", "preferential attachment", "Erdös-Rényi random network"}
- *number-of-friends*: {1, 3, 5}

The key output measure of interest we use is the level of voter satisfaction with the notional elected government at the end of a simulation run, i.e., the proportion of voters within 10% of the centroid of government policies in their two most important issues. In each such diagram the error bars show one standard deviation either way.

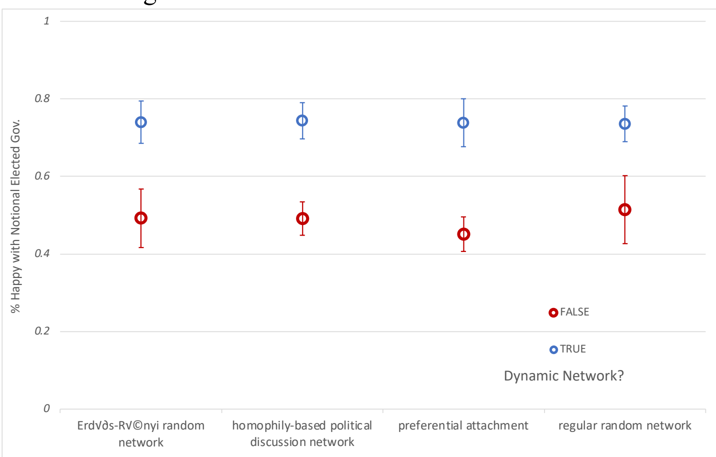


Fig. 6. Overall contrast of dynamic vs. non-dynamic networks for each of four initial network configurations

The significance of the dynamism of the network is evident. For all four different topologies used to initialize the interaction network it clearly makes a difference whether the network evolves during a simulation or not.

The sub-case where it made the most difference was with the following settings:

- *max-salience-change*: 3
- *voter-adapt-prob:* 1
- *max-p-move*: 1
- *discussion-freq*: 2

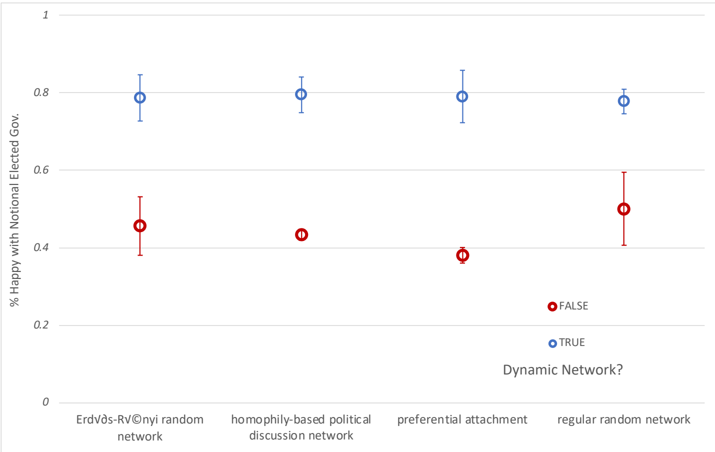


Fig. 7. The sub-case where the dynamism of the network made the greatest difference

The sub-case where it made the least difference was as follows:

- *max-salience-change*: 1.5
- *voter-adapt-prob*: 0.5
- *max-p-move*: 0.5
- *discussion-freq*: 1

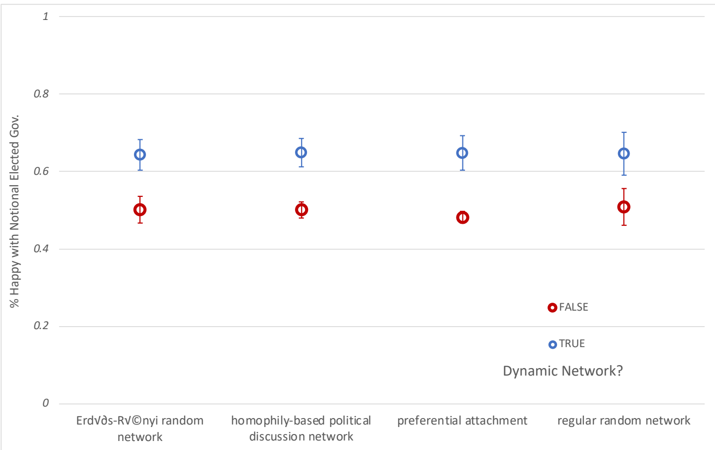


Fig. 8. The sub-case where the dynamism of the network made the least difference

Lower values of the model parameters *max-salience-change*, *voter-adapt-prob*, *max-p-move* and *discussion-freq* result in less difference between dynamic and non-dynamic networks, but this is still a clearly identifiable difference.

5 Conclusion

Our main conclusion is that, given all the other features of the model (many but not all of which were suggested by the available evidence), the network dynamics are essential for producing results like that of the reference case in this model. The opinion dynamics and network dynamics co-evolve and reinforce each other. This echoes the results in some previous models with social influence aimed at understanding political processes, namely the abstract model described in #Edmonds2020 and a more evidence-led model looking at the reasons why people bother to vote # Lafuerza2016. The dynamism of the network makes most difference with more discussion between agents, more adaptivity by voters in terms of attitudes and salience change, and a greater adaptivity from those parties who change policies in response to the voter attitude landscape. Since many models are for theoretical exploration, they tend to focus on *either* social influence of attitudes *or* adaption of social networks. This work suggests that, at least in some empirically-suggested cases that *both* mechanisms might be needed, since they can act to amplify or dampen each other's effects.

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