Agent-Based Model for Media Influence on Election Results

Moritz Bürger[1], Emanuel Jucker[2], Maximilian Spitaler[3], and Linghang Sun[4]

[1]mbuerger@ethz.ch, Student ID: 20-943-981, MSc. Physics
[2]ejucke@ethz.ch, Student ID: 22-933-345, BSc. Mech. Eng.
[3]mspitaler@ethz.ch, Student ID: 24-941-189, MSc. Physics
[4]lisun@ethz.ch, Student ID: 18-948-190, PhD Traffic Eng.

December 16, 2024

Contents

Abstract

This work aims to investigate the impact of media on the opinion dynamics of a simulated election via agent-based modeling. The complex relationship between voters and media is simplified by using a network of voters with hierarchical mutual connections on a two dimensional grid and a separate set of media nodes with random connections to voters. The results reveal a strong media influence on voter opinions, with significant implications for media-driven manipulation. When voters are allowed to choose the media outlets they are listening to, media manipulation becomes ineffective over almost the entire range of media opinions. Only if neutral media nodes are manipulated, a substantial lead of one opinion over the other emerges, suggesting that susceptibility to media manipulation concentrates among undecided voters in the presence of echo chambers.

1 Introduction

1.1 Motivation

This year, elections in more than 70 countries will shape the future of 3.7 billion people [1], underscoring the immense scale and impact of democratic decision-making. Beneath these massive numbers lie the political opinions of individual voters. Taken together, these opinions determine the outcome of an election.
To better understand the dynamics of the elections one must know how those opinions are formed: Key factors include our interests, life experiences and moral values, as well as our peer group and the media we listen to.
The media factor has changed significantly in the last decade. With the rise of the Internet, the average media consumption has increased. Additionally, voters can choose from a much broader media landscape, as they are no longer limited to a handful of print newspapers. This change led to disruptive new political movements and opinion dynamics.
This work aims to better understand these influences. How do opinion dynamics change when media opinions are more polarized? What if they are manipulated, for example, by governments, marketing agencies or social media algorithms? And how does this intertwine with a media feedback mechanism, where individuals can choose which media outlet they follow?

1.2 Related literature

Agent-based models (ABMs) are frequently used to investigate opinion dynamics, electoral outcomes, and media influence. They often draw analogies to physical systems, such as the Ising model, where individuals adopt "spin" states influenced by neighbors and external fields such as media. Galesic & Stein [2] used Ising-models with a 2D voter distribution and spatial localization to simulate opinion formation. They then compared it with real world data and demonstrated that such model can provide a robust framework for understanding opinion formation. Grabowski & Kosiński [3] included mass media to their Ising-models as an external influence to their model. They were able to show numerically, that under certain circumstances mass media could provoke critical rebuilding of the public's opinion.
Recent research also highlights the critical role of media choice in polarization. Benedetto et al. [4] used an Ising-system to examine the effect of people choosing what they listen to. They were able to show that such media feedback mechanism can intensify polarization. If people stop listening to media from the other political side, echo chambers are formed and thus polarization increases.
The network structure is also crucial: Musso & Helbing [5] showed that an absence of long-range connection, resulting in more close-knit communities, increases the socio-diversity of the network. This illustrates that the way a network is setup is crucial to analyze opinion dynamics, for example polarization.
Such Ising-systems are not only applicable to opinion dynamics. Krawiecki and Helbing [6] used a model similar to a random Ising system to model financial markets, demonstrating that such systems can also be applied to other fields. Building on these insights, we focus on how media polarization, manipulation and the media feedback mechanism shapes elections. Our work integrates the network structure based on the Ising system [2] combined with the media influence based on [3, 4] to model and analyze opinion dynamics.

1.3 Research questions

The goal of this project is to better understand the influence of media on voter opinions. Inspired by the work of Benedetto et al. [4], an agent based election model is implemented. This model is based on an Ising system and consists of a grid of 50×50 voters, each with an opinion of either $-1, 0, 1$ (blue, neutral, red). Additionally, there are media nodes with an opinion between -1 and 1. Voters are influenced by other voters and the connected media nodes.
We believe that the polarization of the media and media bias is decisive for the formation of voter opinions. By varying the polarization and introducing a shift in the media bias towards red/blue in our election model and then comparing the different simulation results, this effect can be analyzed. Additionally, a media feedback method is implemented. This allows voters to choose which media they want to listen to by cutting connections to media with opposite opinions and replacing them with new media nodes. We then combine these two things, polarization and bias, and media feedback to study the resulting two-way interaction. Our thinking is that people can counteract bias and affect polarization by choosing what they want to listen to.
In real life, people have multiple opinions on different topics, but only two candidates to choose from. This complexity will be accounted for through the development of a model in which multiple opinions can be held by both voters and the media. This approach enables the analysis of potentially more intricate and realistic interactionsw at a later stage. We are aware of the limitations and simplifications of our model. We will not be able to replicate reality to a degree that would allow for direct real-world application. Nevertheless, this can provide an initial insight into how these processes work, helping to do more detailed analysis in the future.

2 Model

2.1 Network generation

The voter population is generated following a square lattice Ising model with each grid point representing a voter. To demonstrate the voter relationship for opinion influence, connections are created with a hierarchical structure consisting of first- and second-level connections. Voters with a connection between them are referred to as neighbors. The probability of having a total number of k connections for a voter follows the power law so that the network is scale-free, as shown in figure 1c:

$$P(k) \sim k^{-\gamma}, k \in \{k_{\text{min}}, k_{\text{max}}\}$$

where $\gamma = 3$, $k_{\text{min}} = 18$, and $k_{\text{max}} = 52$ are chosen following [4] to represent a more realistic voter population and their number of connections.

The chance of first-level connection, as shown in figure 1a, between any two voters i and j is dependent on the Cartesian distance $l_{ij} = \sqrt{(m_i - m_j)^2 + (n_i - n_j)^2}$ between these voters, where (m_i, n_i) denotes the coordinates of voter i. The probability is negatively correlated with l_{ij} and it follows:

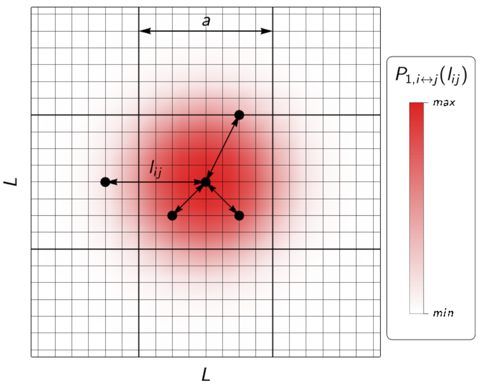
$$P_{1,i\to j}(l_{ij}) \sim \frac{1}{1 + e^{(l_{ij}-a)/b}} + 0.001\frac{L - l_{ij}}{L}$$

where L is the voter square lattice, a is the side length of a voter's local group, and b is defined as $b = a/4$. In this study, the side lengths for the voter square lattice and local group are 50 and 10, respectively, and therefore, the voter population is $N^V = L^2 = 2500$.

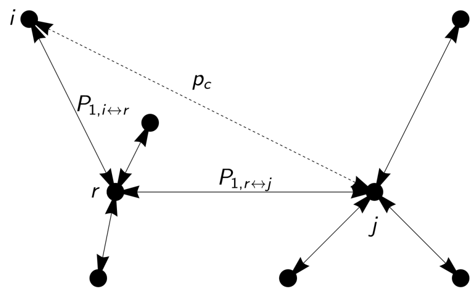
The probability of the second-level connection, as shown in figure 1b, is calculated as:

$$P_{2,i\to j} \sim p_c \sum_{r\in\mathcal{N}} P_{1,i\to r} P_{1,r\to j}$$

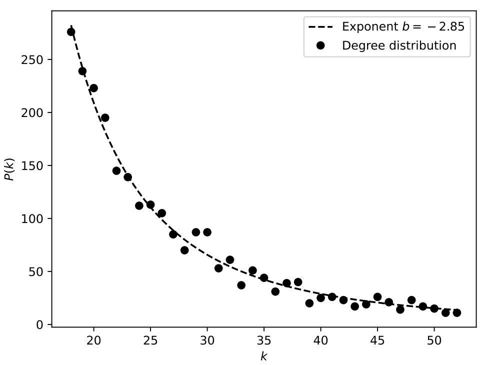
where p_c is a coefficient determining the percentage of the second-level connections. The p_c is selected as 0.01, so roughly 70% of a voter's neighbors are within the same local group, as in figure 1d.



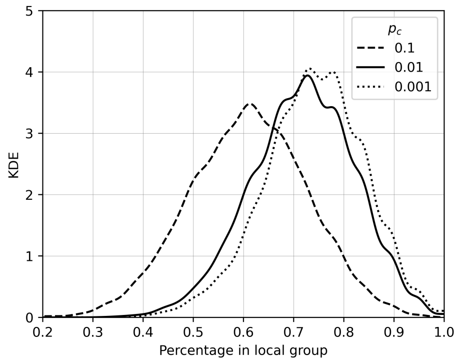
(a) First-level connection



(b) Second-level connection



(c) Distribution of total connections



(d) Distribution of connections in local group

Figure 1: Network generation

In addition to the connections among the voters, another layer of connections between voters and a total number of N^M media outlets is also generated. Each media randomly builds connections with C^M voters. The values of N^M and C^M are calibrated in section 3 and the default values are set to 40 and 350, resulting in an average of voter's $\frac{N^M C^M}{N^V} = 5.6$ connections with media outlets.

Each voter is initialized with one and only one opinion $S_i \in \{-1, 0, 1\}$, where $-1, 0, 1$ shows the voter's preference for the blue party, no voting preference, and preference for the red party, respectively. Each media outlet also has an initial opinion. However, instead of a discrete opinion space similar to voter opinion, media opinion follows a specific distribution function $S_i^M \in [-1, 1]$. Different initial media opinion distribution functions, including normal distribution, $\beta-$distribution, and their results are introduced in section 4.1.

2.2 Update of voter opinion

Every day N^V_{updated} voters $i \in \mathcal{N}$ are randomly selected to update their opinion $S_i \in \{-1, 0, 1\} \equiv \{\text{blue}, \text{neutral}, \text{red}\}$ according to their local environment $\mathcal{N}_i = \mathcal{N}_i^V \cup \mathcal{N}_i^M$ consisting of $n_i^V = \left|\mathcal{N}_i^V\right|$ other voters and $n_i^M = \left|\mathcal{N}_i^M\right|$ connected media nodes $m \in \mathcal{M}$. N^V_{updated} is chosen such that every of the $|\mathcal{N}| = N^V$ voters updates his or her opinion every $t_{\text{updated}} = N^V/N^V_{\text{updated}} = 50$ days on average. The expectation value $\left\langle n_i^M \right\rangle$ of media connections per voter given a total number of $|\mathcal{M}| = N^M$ media nodes (*number media*) and C^M connections per medium can be calculated as

$$\left\langle n_i^M \right\rangle = \frac{N^M \cdot C^M}{N^V} \sim 5.6 \; .$$

According to the previous section 2.1,

$$\left\langle n_i^V \right\rangle = \int_{k_{min}}^{k_{max}} P(k) k \mathrm{d}k \sim 26.5 \; .$$

Compared to voters, media nodes have a stronger influence on the opinion formation process, which is modeled by a weighing factor (*media authority* W)

$$W_j = \begin{cases} 1, & j \in \mathcal{N}_i^V \\ W, & j \in \mathcal{N}_i^M \end{cases} .$$

In total, the influence of the environment of voter i is captured by the local field h_i that determines whether the opinion is changed or not.

$$h_i = \frac{\sum_{j \in \mathcal{N}_i} W_j S_j}{\sum_{j \in \mathcal{N}_i} W_j}$$

If h_i is in a certain relation to the threshold $T(S_i \to S_i', \langle S_i \rangle)$ which itself depends on the current opinion of the voter S_i and the total voter polarization $\langle S_i \rangle$ of the network via the proportionality constant (*threshold parameter*) α, the opinion is changed from S_i to S_i'. In general, transitions $S_i \to S_i'$ are only allowed from voter to non-voter or vice versa. Starting from the initial values $T^0_{NV \to V}$ and $T^0_{V \to NV}$, the threshold values $T_{V,NV \to NV,V}$ are shifted to make transitions towards the majority opinion harder. They follow the form

$$T_{V,NV \to NV,V} = T^0_{V,NV \to NV,V} \pm \alpha \langle S_i \rangle \; .$$

For $S_i' > S_i$ (transition towards red), h_i has to be $> T(S_i \to S_i', \langle S_i \rangle)$ to change opinion. Additionally, if $\langle S_i \rangle > 0$ the initial threshold is increased to make changes harder (i.e. they require a stronger polarized environment and therefore a larger h_i).

$$T_{B \to NV} = T^0_{V \to NV} + \alpha \langle S_i \rangle$$
$$T_{NV \to R} = T^0_{NV \to V} + \alpha \langle S_i \rangle$$

For $S_i' < S_i$ (transition towards blue), h_i has to be $< -T(S_i \to S_i', \langle S_i \rangle)$ to change opinion. In case $\langle S_i \rangle > 0$, the initial threshold is decreased/stays constant to make changes easier (i.e. they require a less polarized environment).

$$T_{R \to NV} = T^0_{V \to NV}$$
$$T_{NV \to R} = T^0_{NV \to V} - \alpha \langle S_i \rangle$$

The shift of the threshold is directly opposite if $\langle S_i \rangle < 0$. On top of the threshold mechanism, the threshold value $T(S_i \to S_i', \langle S_i \rangle)$ is bound by 0 and 0.5.

2.3 Evaluation metrics

The quantities we use to characterize our model are:

- the share of voters and media with opinion $S \in \{-1, 0, 1\}$ $\tilde{n}_S$ and $\tilde{m}_S$

$$\tilde{n}_S = \frac{|\{i \in \mathcal{N} : S_i = S\}|}{N^V} \qquad \tilde{m}_S = \frac{|\{i \in \mathcal{M} : \mathcal{G}(S_i^M) = S\}|}{N^M} \qquad \mathcal{G}(S_i^M) = \begin{cases} 1, & S_i^M \in [1, 1/3) \\ 0, & S_i^M \in [1/3, -1/3] \\ -1, & S_i^M \in (-1/3, -1] \end{cases}$$

- average values of the voter and media opinion $\langle S_i \rangle$ and $\langle S_i^M \rangle$ and the corresponding standard deviations

$$\langle S_i \rangle = \frac{1}{N^V} \sum_{i \in \mathcal{N}} S_i \qquad \langle S_i^M \rangle = \frac{1}{N^M} \sum_{i \in \mathcal{M}} S_i^M$$

$$\sigma_{\langle S_i \rangle} = \frac{\sqrt{\langle S_i^2 \rangle - \langle S_i \rangle^2}}{\sqrt{N^V}} \qquad \sigma_{\langle S_i^M \rangle} = \frac{\sqrt{\langle (S_i^M)^2 \rangle - \langle S_i^M \rangle^2}}{\sqrt{N^M}}$$

- the average opinion of neighbors x_i^N for each voter i

$$x_i^N = \frac{1}{n_i^V} \sum_{j \in \mathcal{N}_i^V} S_j$$

- the clustering coefficient $\langle c_i^V \rangle$

$$c_i^V = \frac{1}{n_i^V} \sum_{j \in \mathcal{N}_i^V} c_{ij} \qquad c_{ij} = \begin{cases} 1, & S_i = S_j \\ 0, & S_i \neq S_j \end{cases} \qquad \langle c_i^V \rangle = \frac{1}{N^V} \sum_{i \in \mathcal{N}} c_i^V$$

- the probability to change opinion P (average opinion changes per year per voter), where $p_i(t)$ denotes an opinion change of voter i at time step t and the average is taken starting from t_0 over T time steps

$$P = \frac{1}{N^V} \sum_{i \in \mathcal{N}} \frac{1}{T} \sum_{t=t_0}^{t_0+T} p_i(t)$$

2.4 Update of media opinion

Each of the N^M media nodes is assigned an opinion $S_i^M \in [-1, 1]$ and a random set of voters $\mathcal{V}_i$ with $|\mathcal{V}_i| = C^M$ fixed. The distribution of initial media opinions is equally spaced over the entire interval $[-1, 1]$ (*reference case*) or sampled from probability distribution (see 4.1 Initial media distribution). In any case, it has to be made sure that $\langle S_i^M \rangle = 0$.
After initialization, the media opinion is updated based on two terms. Firstly, the influence of external parameters which are not controlled is modeled by a randomly fluctuating term which is added to the opinion of each media node every day (*economy term*). It is taken from a normal distribution centered at zero $N(0, \sigma_{ec})$. Secondly, once every t_{period} days, a boredom term (*duration term*) is added shifting the media towards the minority opinion. It grows accumulatively with the number of consecutive terms by 25% of the initial value for each consecutive term and is bound by 3 times the initial value. In figure 2, the effect of these terms on the media opinion $\langle S_i^M \rangle$ is illustrated. Whenever red (blue) hold the majority among the voters, the media tend to shift towards -1 (1) as expected from the *duration term*.
This model for updating the media is adapted from Fair's presidential vote equation [7] in accordance with the form proposed in [4]. In particular, influence of wars, the bias term and the advantage of the presidential incumbent is neglected since the model only contains parties and no politicians and the economic terms are grouped together.

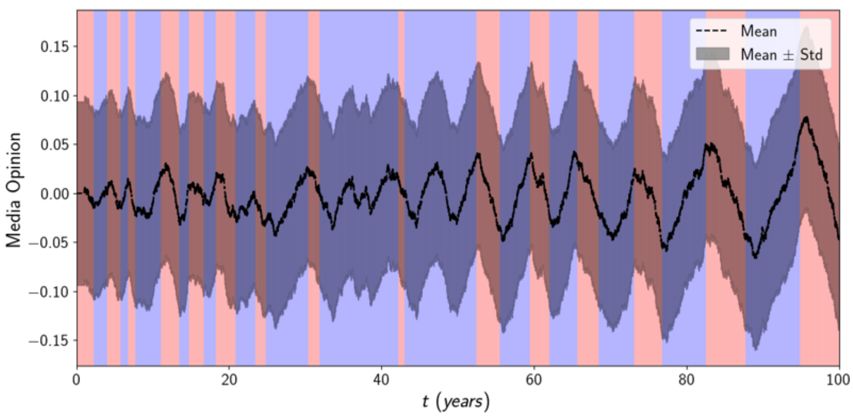


Figure 2: Average media opinion $\langle S_i^M \rangle$ and standard deviation (gray) plotted together with the majority party (red/blue)

2.5 Media feedback

Media feedback allows the set of media connections per voter $\mathcal{N}_i^M$ to be changed based on the voter's opinion S_i. For each disagreeing media node $\{j \in \mathcal{N}_i^M : \text{sgn}(S_j^M) \neq S_i\}$ it is decided with probability β (*media feedback parameter*) to cut the connection and replace it with a random new one j' if it agrees with the voter's opinion. Hereby, the number of media connections per voter n_i^M is kept constant. For neutral voters, media opinions $|S_j^M| \leq 0.1$ are considered agreeing media nodes.

3 Calibration

Altogether, the following free parameters need to be calibrated:

- *number media* N^M
- *media authority* W
- *initial threshold* $T^0_{NV\to V}$ and $T^0_{V\to NV}$
- *threshold parameter* α
- *media feedback parameter* β

For the calibration, the relevant criteria we choose are that the model yields approximately equal shares of red and blue voters. In particular, situations where one opinion dominates with nearly 100% need to be avoided. Moreover, based on historic election data, a non-voter share of 40% should be reproduced [8].

With increasing initial threshold values $T^0_{NV\to V}$ ($T^0_{V\to NV}$) we see that the number of non-voters increases (decreases) since it becomes harder to leave (enter) this group. With more polarized voters (red/blue) the standard deviation of the average voter opinion also grows and therefore behaves directly opposite to the number of non-voters. With a high $T^0_{NV\to V}$ (and small $T^0_{V\to NV}$) there is an increase in clustering because of the large number of non-voters. A similar effect is not observed for $T^0_{V\to NV}$ because it equally increases the tendency to stay in the red and blue voter group. If $T^0_{V\to NV}$ becomes equal to $T^0_{NV\to V}$ the increase in clustering is suppressed (figure 3a).

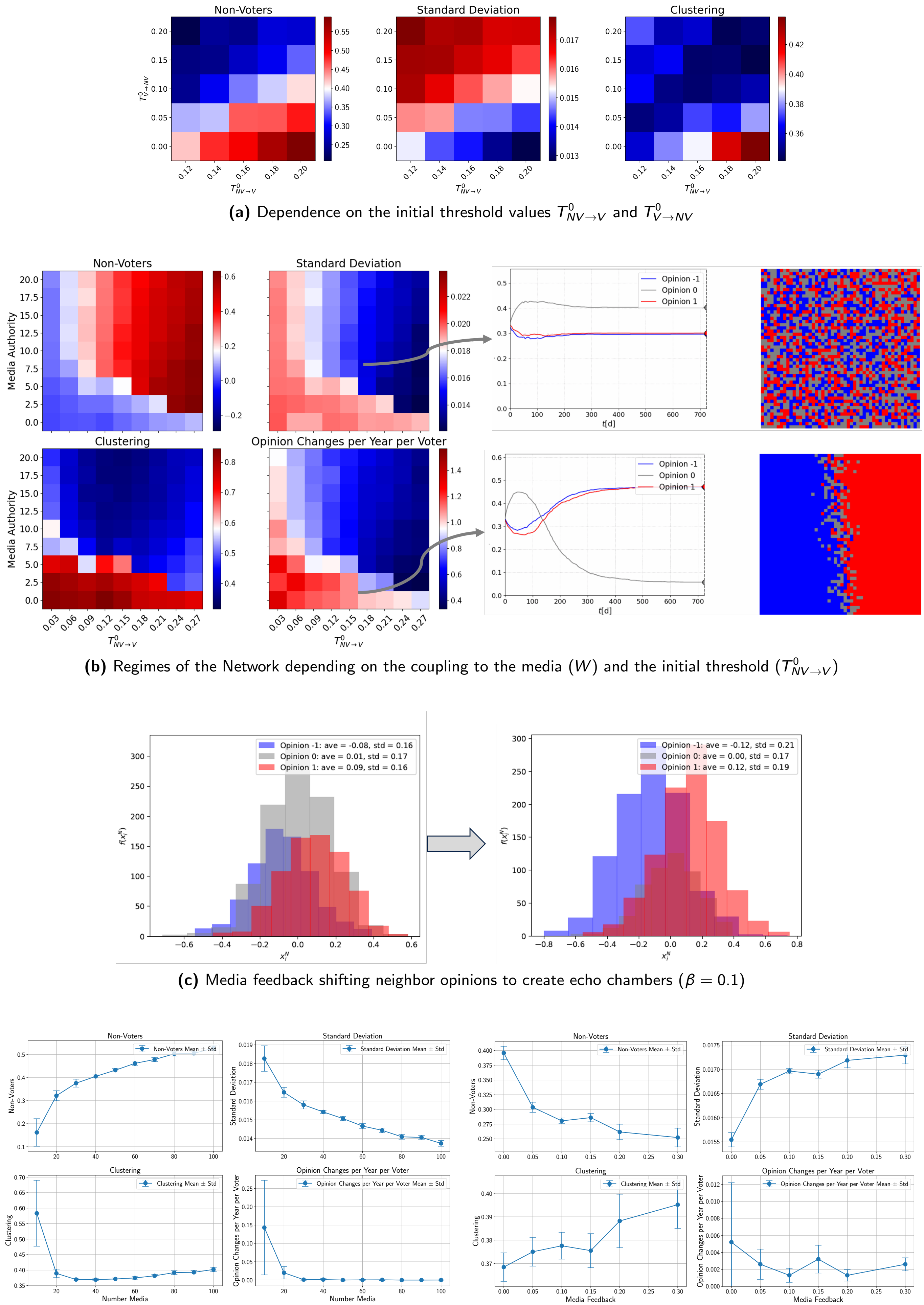
The coupling strength between voters and media is described by the number of media N^M and the media authority W. With increasing W and N^M the coupling is increased and therefore, connections to other voters are relatively less important. As a consequence, the number of non-voters increases and there is no spatial separation in a red and blue voter group. Hence, the clustering is reduced abruptly when the coupling to the media is increased (either by increasing N^M or W). The two different media coupling regimes can be clearly visualized together with the dependence on the initial threshold value in a heatmap as seen in figure 3b. With strong media coupling and a higher initial threshold value, the tendency to change opinion (as given by the average opinion changes per year per voter) is also reduced. Figure 3d illustrates the effect of the number of media N^M. As expected, it shows the same behavior as the media authority W (drop in clustering, more non-voters and smaller probability to change opinion) since both determine the coupling to the media.

All these calibrations are all performed without media feedback present. Upon activation of the media feedback mechanism, the share of neutral voters is reduced compared to the initially calibrated 40%. Media connections are no longer fixed and the relative voter influence is higher. Voters therefore tend to be surrounded by more voters of the same opinion. This is illustrated in the histogram of average neighbor opinions x_i^N in figure 3c. Media feedback shifts the neighbors of red voters more towards red and vice versa for blue voters. Consequently, the clustering rises with the feedback strength β as illustrated in figure 3e. Therefore, media feedback leads to the creation of echo chambers and due to this, voters are less likely to change their own opinion (reduced number of annual opinion changes per voter). Moreover, it should be noted that with media feedback, the network takes much longer to reach equilibrium. Consequently, the time steps t_{model} have to be increased by a factor of 10 to obtain stable results.

A summary of the chosen parameters based on our calibration is given in table 1.

Table 1: Default parameters

Parameter	Value
number media N^M	40
number media connections n_i^M	350
media authority W	10
initial threshold $T^0_{V\to NV}$	0
initial threshold $T^0_{NV\to V}$	0.16
threshold parameter α	0.5
media feedback parameter β	0.1



(a) Dependence on the initial threshold values $T^0_{NV\to V}$ and $T^0_{V\to NV}$

(b) Regimes of the Network depending on the coupling to the media (W) and the initial threshold ($T^0_{NV\to V}$)

(c) Media feedback shifting neighbor opinions to create echo chambers ($\beta = 0.1$)

(d) Dependence on the number of media N^M (averaged over 12 runs)

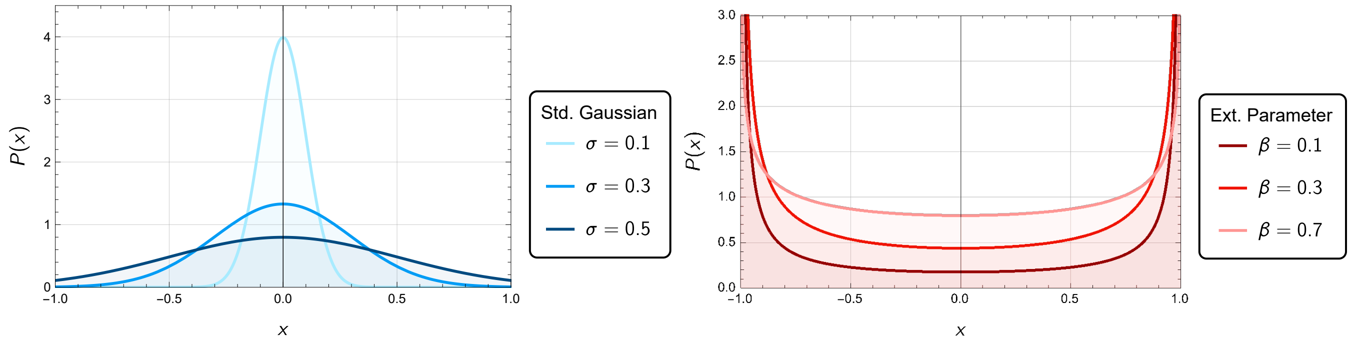
(e) Dependence on the media feedback parameter β (averaged over 4 runs)

Figure 3: Network calibration

4 Results and Discussion

4.1 Initial media distribution

Different initial media distributions shift the relative share of mainly neutral $S_i^M \in [-1/3, 1/3]$, mainly blue $S_i^M \in [-1, 1/3)$ and mainly red $S_i^M \in (1/3, 1]$ media nodes. Compared to the reference case of equally spaced media opinions, this can be achieved by sampling the opinions from a normal distribution centered at 0 with varying standard deviation σ $S_i^M \sim N(0, \sigma)$ to increase the share of neutral media nodes. On the other hand, using a β-distribution shifted to $[-1, 1]$ with equal parameters results in more media nodes close to -1 and 1 as seen in figure 4.
Starting from the reference case with equal share of each media group, the number of neutral media is substantially increased with lower σ values. From figure 5a it can clearly be seen that the number of non-voters also rises with smaller σ. This reflects the immediate influence of media opinions on the network of voters. With less neutral media (i.e. less non-voters and higher σ), the standard deviation of the average opinion increases because there are more polarized (red/blue) voters. Due to the redistribution of non-voters to red and blue with higher σ, the clustering decreases.
On the other hand, with more polarized media (figure 5b) the number of non-voters drops. The higher the degree of polarization (the lower β), the less non-voters there are. Because non-voters are shifted equally to red and blue with lower β, there is no increase in clustering. Moreover, no significant trend in the probability to change opinion with different initial media distributions can be observed.



(a) Normal distribution favoring neutral media **(b)** β-distribution favoring red/blue media

Figure 4: Initial media opinion distribution

4.2 Shift of media opinion

When considering the manipulation of media nodes, three key variables can be adjusted:

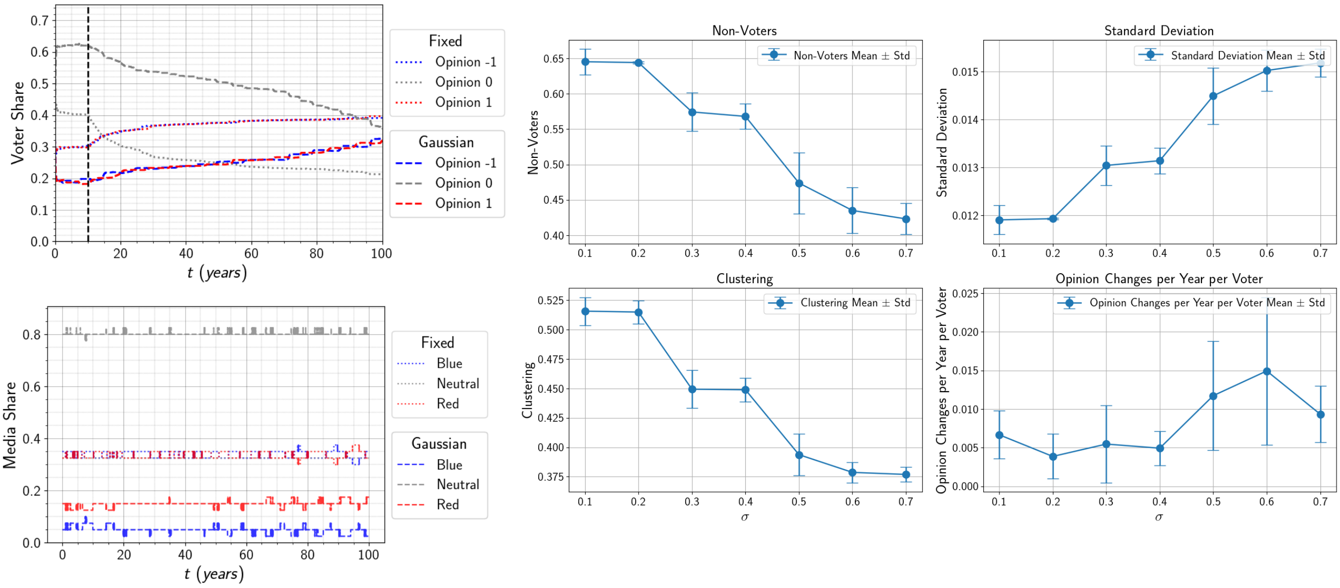
1. *Magnitude of the Shift (s)*: This represents the amount by which the opinion of the media nodes are shifted.
2. *Number of Media Nodes Shifted (N)*: This is the count of media nodes that are shifted by s.
3. *Selection of Media Nodes*: media nodes can be chosen for manipulation based on their opinions. For this, a *target opinion* (S_{target}^M) can be defined.

Furthermore, it is useful to combine the magnitude of the shift s and the number of shifted media nodes N into a single new quantity, called *Manipulation Factor (M)*, calculated as $M = N \cdot s$. This means that for constant M the change in the average opinion of the media landscape is the same. (Except for the case where the manipulation is limited by the fact that the most extreme opinions that are possible are 1 and -1 respectively).

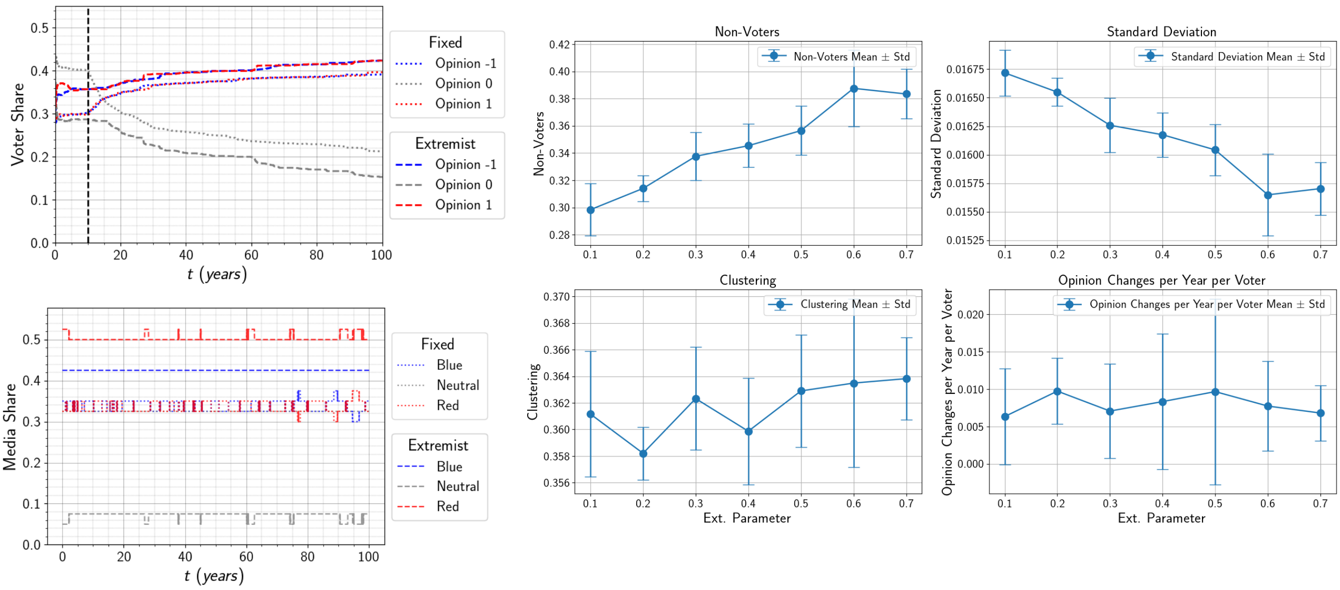
The impact of media node manipulation is assessed by analyzing its influence on the voter population. This is specifically measured by observing the *average lead of the share of red voters $\tilde{n}_1$ over the share of blue voters $\tilde{n}_{-1}$* in the years Δt following the manipulation in year t. This will be denoted as $\Delta = \langle \tilde{n}_1 - \tilde{n}_{-1} \rangle_{[t, t+\Delta t]}$.

For the following results, the Manipulation Factor M is fixed to achieve comparable results. The two variables that are examined are the number of media nodes and the target opinion. This means that for each configuration in this parameter space, the N media nodes which are closest to the target opinion $S_{\text{target}}^M \in [-1, 1]$ are selected and shifted according to M. For all of the following data that is presented $M = 0.8$ is chosen, because it turns out to be big enough to cause measurable effects in the voter population, but small enough to keep the system functioning. Given the inherent random nature of the system, it is necessary to take multiple runs for each of configuration of the two dimensional parameter space to obtain reliable results. Furthermore, $\Delta t = 1$ year for the calculation of all leads Δ.

An example of what the results of these simulations look like is given in figure 6. Here, the different lines represent different target opinions applied to a single media node ($N = 1$). The results are averaged over 8 independent simulation runs. Two scenarios are analyzed: one without media feedback and another with media feedback. In the absence of feedback (left panel), the influence of the manipulated media node has a noticeable effect for a wide range of target opinions. However, when media feedback is enabled (right panel), the impact of the manipulation is negligible for all the displayed target



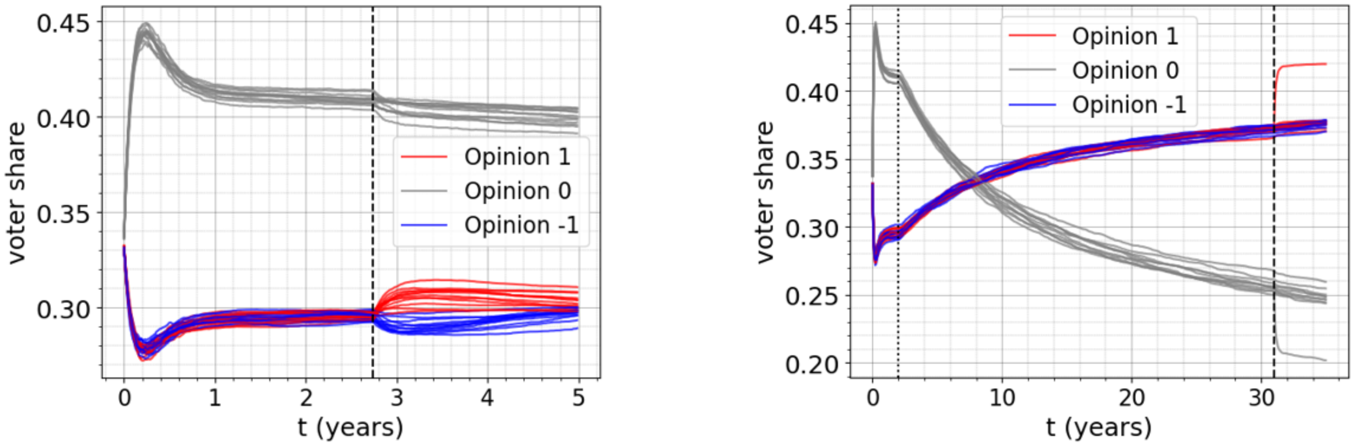
(a) Results for a normal distribution of initial media opinions (averaged over 3 runs). Left panel: voter and media share for $\sigma = 0.25$.



(b) Results for a β-distribution of initial media opinions (averaged over 6 runs). Left panel: voter and media share for $\beta = 0.1$

Figure 5: Dependence of the network on the initial media distribution. The left panels show the voter and media share with media feedback initialted after 10 years. The right panel gives the effect of different parameters σ and β on the network characteristics (without media feedback)

opinions, but one. Furthermore, if no media feedback is present, the share of red voters rises and the share of neutral and blue voters decreases. However, when media feedback is activated the only scenario where significant change happens sees the share of red voters rise, while the share of neutral voters plummets and the share of blue voters remains virtually unchanged.



(a) Without media feedback. **(b)** With media feedback.

Figure 6: The time evolution of the voter population after media manipulation. The dashed line indicates the media node opinion shift. The dotted line indicates the activation of media feedback.

The experiments investigate the impact of shifting the opinion of media nodes on voter opinion dynamics. Figure 7 displays Δ for a range of different N and S^M_{target} in the case of no media feedback. For large N there is no longer any significant dependence on S^M_{target}, this is because the effect of S^M_{target} is generally washed out, when a large number of media nodes is picked, as these nodes are more spread out in the opinion space. In addition to that, for many target opinions, the media nodes that are selected based on the target opinion are actually the same, especially for target opinions that are close to 1 or -1 respectively.
Also changes in N matter most when N is small. The regime of $N \in [1, 4]$ displays the most interesting behavior, a more detailed investigation of this is shown and discussed in figure 8.

This analysis examines the effect of varying the number of manipulated media nodes and their target opinions under two distinct conditions: without media feedback and with media feedback. In figure 8 the effect of media manipulation can be seen as a function of both N and S^M_{target}. The left panels of Figure 8 illustrate the results in the absence of feedback. Here, the impact of media manipulation is strongest for $N = 1$. The intensity of the shift diminishes as the number of manipulated media increases. There is a decrease in Δ for $S^M_{\text{target}} > 0.3$ and $N = 1$. This is logical, as the maximum for the opinion a media node can have is 1. Any target opinion S^M_{target} that leads to the selection of a media node with an opinion S^M_i such that $s + S^M_i > 1$ is inefficient because the new opinion cannot be greater than 1. This inefficiency is given by $\max(0, S^M_i + s - 1)$. It prevents a strong impact on the voter population for high S^M_{target} and low N. With an increase in N and the corresponding decrease in s, the decrease in Δ is delayed to a higher target opinion S^M_{target} accordingly.

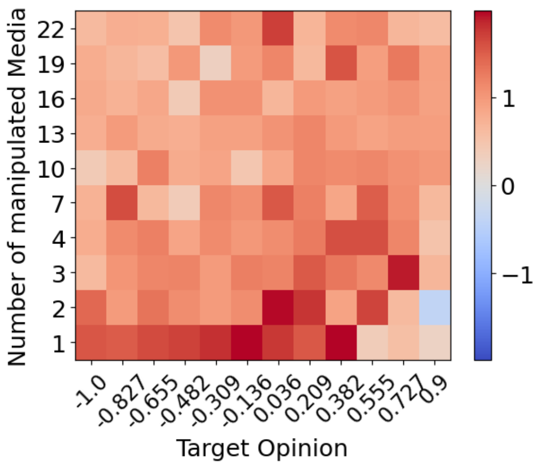
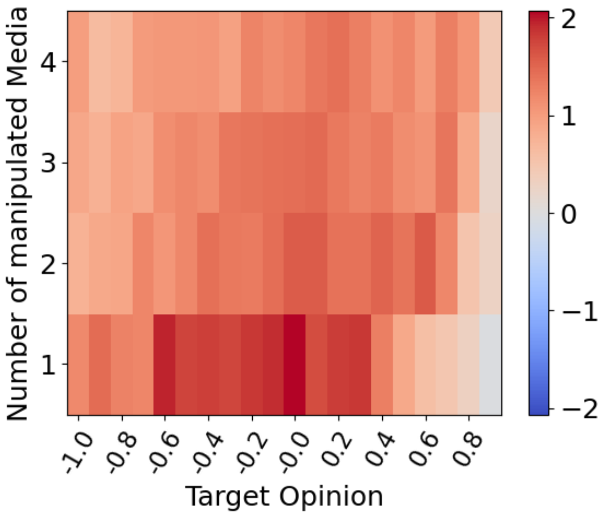


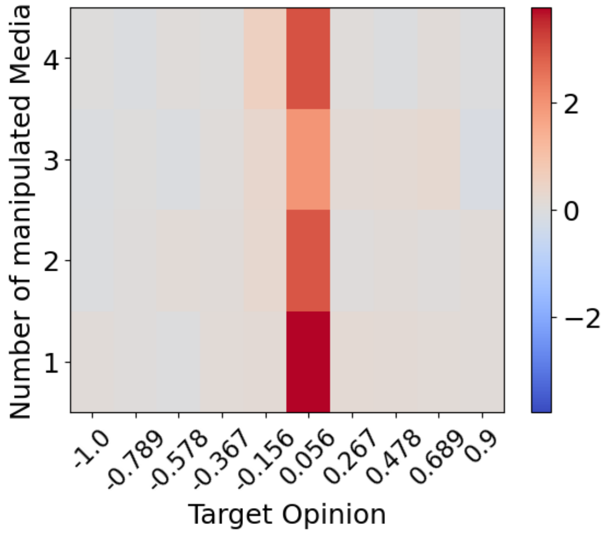
Figure 7: Average lead Δ, in percentage points. No media feedback. Averaged over 8 runs per data point.

In contrast, the right panels of Figure 8 show the scenario with media feedback enabled. A striking difference is observed. The media manipulation only is effective for a narrow range of target opinions which are close to 0. The number of manipulated media nodes matters less in the scenario with media feedback than for the scenario without media feedback in the regime of $N \in [1, 4]$. However, $N = 1$ remains most effective. The width of the peak of Δ is limited by the resolution of the target opinions, rather than by the system itself.

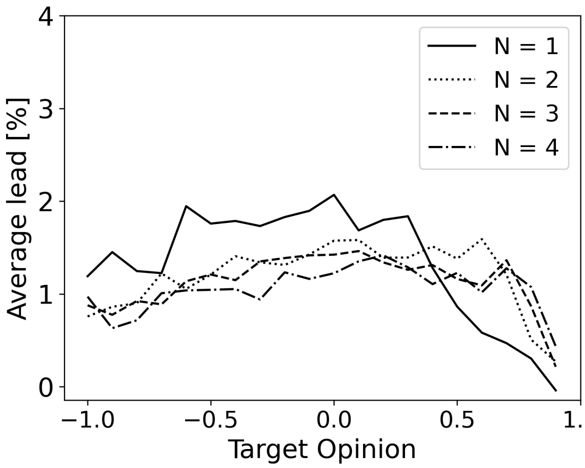
One possible explanation for the stark differences may be that neutral voters are the most susceptible target group for media manipulation. This may be because they are most likely to live in neighborhoods that are neutral or mixed, rather than predominantly red or blue. Even without media feedback, neutral media nodes are more likely to have connections to neutral voters, because of their own influence on them. The media feedback mechanism enables neutral voters to remove media nodes that do not agree with their opinion. This means that the correlation between the opinion of the media nodes and the voters that are connected to them is much stronger than without media feedback. It is worth noting that



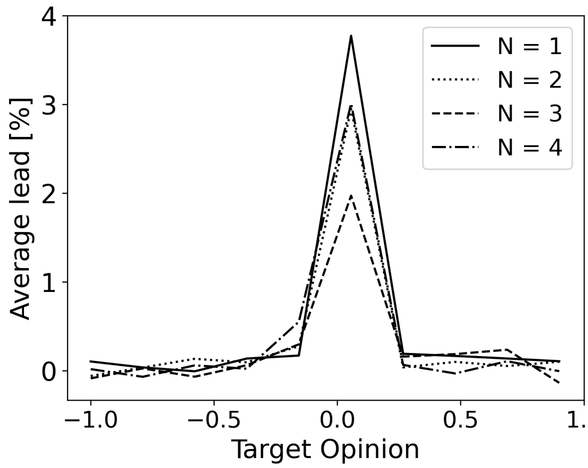
(a) Average lead Δ, in percentage points. No media feedback. Averaged over 20 runs per data point.



(b) Average lead Δ, in percentage points. With media feedback. Averaged over 8 runs per data point.



(c) No media feedback. Averaged over 20 runs per data point.



(d) With media feedback. Averaged over 8 runs per data point.

Figure 8: The images illustrate experimental results on media manipulation, comparing scenarios without (left) and with (right) media feedback, with the lead Δ evaluated for varying N and t values.

$S^M_{\text{target}} = 0.056 \in [-0.1, 0.1]$. This means that the only target opinion S^M_{target} for which a meaningful lead Δ can be achieved is also the only one that is contained in the interval that is tolerated by neutral voters. In addition, media feedback leads to a bigger polarization of the voting population and a higher clustering coefficient. Therefore, media feedback further increases the likelihood that red or blue voters live in neighborhoods dominated by like-minded voters, which makes it harder for them to change their opinion.

Media feedback can strongly inhibit the effects of manipulation, as voters may disconnect from media that deviates too far from their views. If media nodes fail to quickly change the opinions of their connected voters, they risk losing influence entirely. This explains why media feedback can significantly reduce the effectiveness of media manipulation.

5 Outlook

5.1 Opinion multi-dimensionality

The decision-making process for casting a vote often extends beyond a straightforward preference for one party over another. It typically involves assessing the policies of both parties. To capture this complexity, we introduce opinion (or policy) multi-dimensionality, which reflects the possibility that a voter may align partially with the policies of a given party.

As shown in figure 9, the one-dimensional opinion case can be illustrated by a line with voter opinion being discrete $S_i \in \{-1, 0, 1\}$ while media opinion, as illustrated by the nodes along the line, being continuous $S_i^M \in [-1, 1]$. To expand the one-dimension opinion scheme into two dimensions, a plane opinion representation is proposed and the voter opinion is defined as $S_i = (s_i^1, s_i^2)$ with $s_i^1, s_i^2 \in \{-1, 0, 1\}$. Hence, while $S_i = (-1, -1)$, $S_i = (0, 0)$, and $S_i = (1, 1)$ still follow the same color and stand for the voter's preference for the blue party, no preference, as well as the preference for the red party, a voter can also agree with only one policy of a specific party, but disagree with the other, reflected by light blue $S_i \in \{(-1, 0), (0, -1)\}$, light red $S_i \in \{(1, 0), (0, 1)\}$, or even show a conflicted opinion $S_i \in \{(-1, 1), (1, -1)\}$.

For simplicity, an assumption is made for the media opinion that their opinions distribute along the solid black diagonal line of the opinion plane, i.e., $S_i^M = (s_i^{M,1}, s_i^{M,2})$ and $s_i^{M,1} = s_i^{M,2}$. The media exerts a pulling effect to attract voters from the purple ends to the media diagonal line. On the other hand, the same opinion update threshold mechanism is also adopted here, indicating that non-voters and conflicted voters are more unwilling to shift towards blue or light blue when the blue party is in power. This effect can be illustrated by another dashed black diagonal line, attracting voters from the other two ends to the said line.

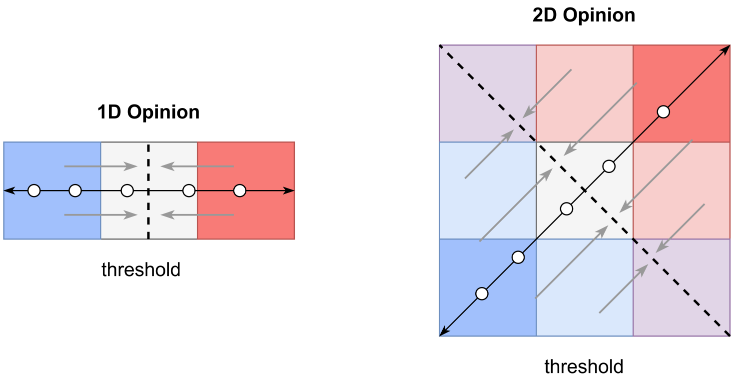
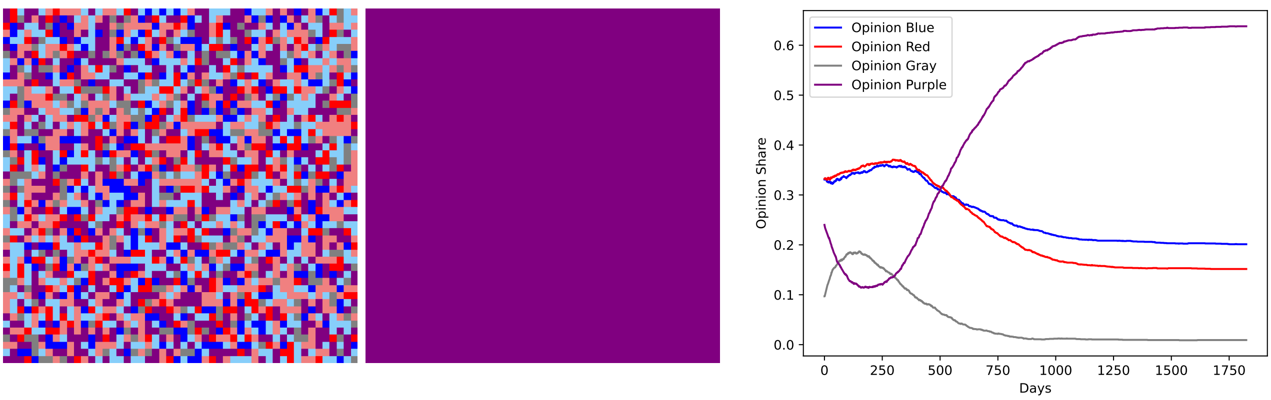


Figure 9: Expanding one-dimensional opinion into two-dimensional opinions

Similar to the thorough calibration implemented in the previous section 3, the first experiment for opinion dimensionality tested different parameters, particularly the media weight. Interestingly, as figure 10 shows, the proportion of the conflicted voters, represented in purple color, first decreased and after approximately 250 days in simulation, their share started to increase and quickly dominated the whole voter population. The results indicate that if there is little influence from the media outlets, then the population will all become conflicted voters, which is not methodologically sound and does not resemble reality, since even without media influence, the majority of the voters should still be able to vote for a party.

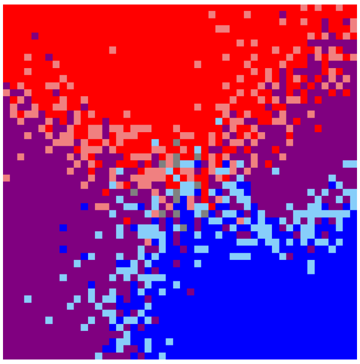


(a) Initial network **(b)** Final network **(c)** Opinion share

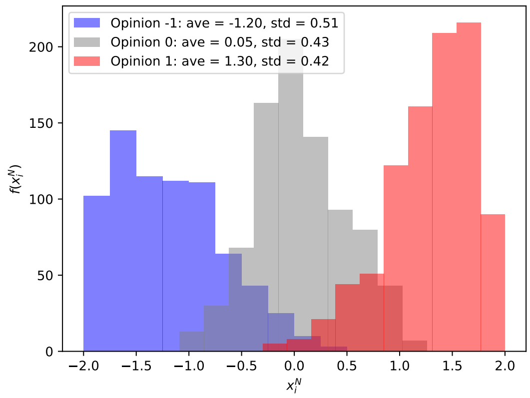
Figure 10: Opinion evolution with opinion multi-dimensionality

This phenomenon of purple wave can be explained by the competing effect between the media influence and the threshold mechanism, represented by the solid media diagonal line and the dotted threshold diagonal line in figure 9. When the media influence is weak, the threshold mechanism makes it easier for the voters to shift toward conflicted opinions instead of becoming true non-voters. To counter this unrealistic performance, another layer of the threshold mechanism should also be added to the conflicted opinions, essentially overlapping the existing media diagonal line. However, for such a new threshold mechanism to function and comply with real-world opinion dynamics, new parameters have to be calibrated. The said calibration process can be computationally demanding particularly considering the codependency between the new threshold and media parameters. Hence, a workaround was tested with the new threshold parameters adopting the same parameters for the one-dimensional threshold, meaning instead of blue and red parties, the two purple zones $\{(-1,1),(1,-1)\}$ are also considered as parties. Consequently, when either purple opinion becomes the dominating preference, the voters would be more inclined to shift to other parties.

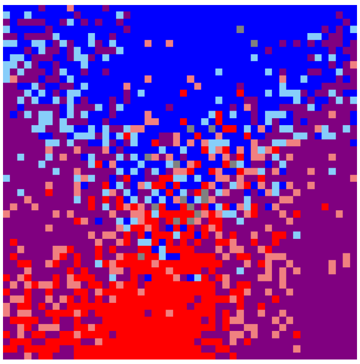
With the new threshold, another two sets of scenarios with a simulation time of three years are tested, i.e., under the baseline scenario and with media feedback, where voters can cut their unfavorable media outlets and build favorable ones over time. In addition, both weak and strong media weights are tested, particularly to showcase the effectiveness of the new threshold mechanism to maintain a good diversity of voter opinions when the media influence is low. Figure 11 shows the results of the baseline scenario and with media feedback under lower media weight $W = 2$. While figure 11a and figure 12a showcase the networks after the simulation, figure 11b and figure 12b illustrate the share of voters with blue, gray, and red each representing both blue and light blue voters, non-voter and conflicted voters, as well as red and light red voters, respectively. As the media influence is low, little difference can be observed between the baseline case and media feedback.



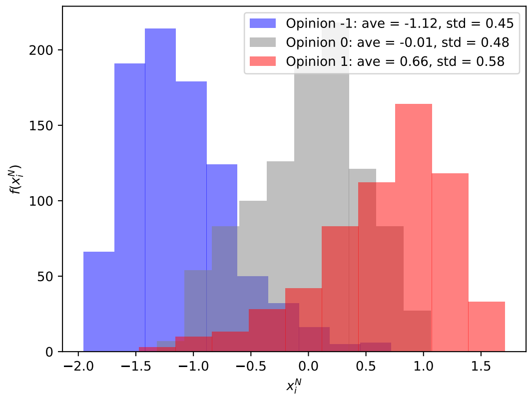
(a) Final network



(b) Opinion distribution without media feedback



(c) Final network

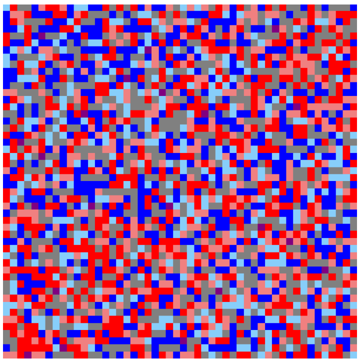


(d) Opinion distribution with media feedback

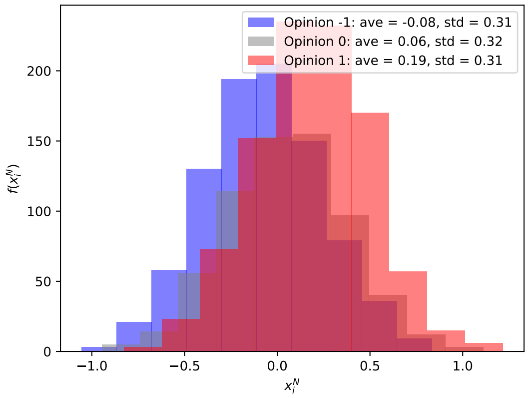
Figure 11: Baseline and with media feedback with low media weight W

However, when the media influence is strong $W = 10$, one pattern can be clearly observed from the final network in the baseline scenario in figure 12a is that few conflicted voters can be seen as well as a relatively lower percentage of light blue and light red voters. For the simulation with media feedback, such a phenomenon is even more pronounced, with barely any light blue, light red, and conflicted voters. Since the majority of voters are either blue or red voters, this is also strong evidence of the existence of the echo chamber effect under opinion multi-dimensionality.

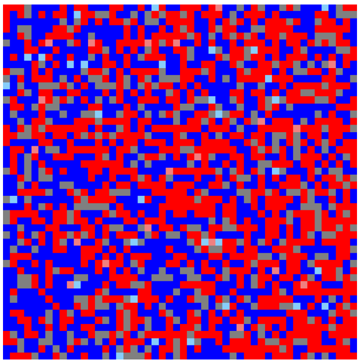
The opinion multi-dimensionality can further be extended with more delicate parameter calibration for both the opinion threshold for the blue and red voters as well as for the purple voters. Moreover, the effect and strategy of shifting media opinion to shift the opinion of the general public can also be studied at a higher level of opinion dimensions.



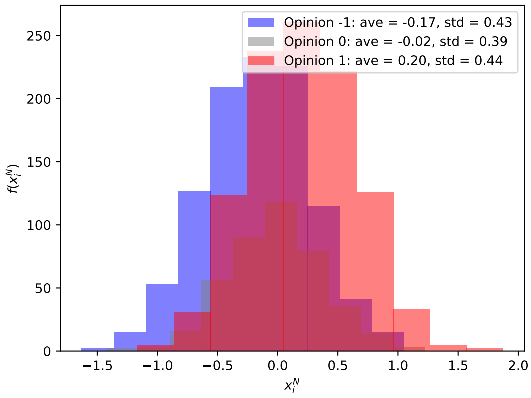
(a) Final network



(b) Opinion distribution without media feedback



(c) Final network



(d) Opinion distribution with media feedback

Figure 12: Baseline and with media feedback with high media weight W

5.2 Future works

A more detailed analysis of the voter population's reaction to the shift in media opinion, that includes an analysis of the entire grid rather than averages of voter shares can clarify by which mechanisms the media feedback causes such drastically different outcomes. Another thing that deserves further investigation is the time evolution of the voter shares after the media manipulation. In the case without media feedback, that can be seen in figure 6a, one can observe that the lead Δ starts to decay again. This can be explained by the boredom term for the media notes, which prevents one party from gaining a permanent majority. However, at least on the time scale that was investigated, this is not the case and the lead Δ remains stable if media feedback is turned on, as can be seen in figure 6b. Thus, it would be interesting to run these experiments for longer times, in order to see if Δ eventually decreases in the case of media feedback, if so it would be worthwhile to characterize the respective timescales of the decay for both cases.

6 Conclusion

By using a voter network with hierarchical connections and a separate set of media nodes, the opinion dynamics of an election model with calibrated parameters is investigated. It is found that media plays a pivotal role in shaping voter opinion dynamics.

Manipulating certain media nodes causes a shift in the voter polarization. This effect is most pronounced if only a small number of media nodes is manipulated. When voters are free to choose their media connections based on their opinions, substantial changes are observed. Only manipulating neutral media effectively alters the voter polarization as undecided voters are most susceptible to media influence. This points towards a diminished effectiveness of media manipulation of voters when echo chambers are formed and suggests that voter autonomy in media selection can act as a buffer against media-driven manipulation. The extension of the model to multidimensional opinions presents a promising avenue for future research, particularly in understanding whether similar dynamics occur in more complex opinion spaces.

References

[1] United Nations Development Programme. *A 'super year' for elections*. https://www.undp.org/super-year-elections. (Visited on 12/16/2024).

[2] Mirta Galesic and D.L. Stein. "Statistical physics models of belief dynamics: Theory and empirical tests". In: *Physica A: Statistical Mechanics and its Applications* 519.C (2019), pp. 275–294. DOI: 10.1016/j.physa.2018.12.0. URL: https://ideas.repec.org/a/eee/phsmap/v519y2019icp275-294.html.

[3] A. Grabowski and R. A. Kosiński. "Ising-based model of opinion formation in a complex network of interpersonal interactions". In: *Physica A: Statistical Mechanics and its Applications* 361.2 (Mar. 2006), pp. 651–664. ISSN: 0378-4371. DOI: 10.1016/j.physa.2005.06.102. URL: https://www.sciencedirect.com/science/article/pii/S0378437105007296 (visited on 11/04/2024).

[4] Andrea Di Benedetto et al. "Media preference increases polarization in an agent-based election model". In: *Physica A: Statistical Mechanics and its Applications* 626 (Sept. 2023), p. 129014. ISSN: 0378-4371. DOI: 10.1016/j.physa.2023.129014. URL: https://www.sciencedirect.com/science/article/pii/S0378437123005691 (visited on 10/23/2024).

[5] Andrea Musso and Dirk Helbing. "How networks shape diversity for better or worse". In: *Royal Society Open Science* 11 (May 2024). DOI: 10.1098/rsos.230505.

[6] A Krawiecki, Janusz Hołyst, and Dirk Helbing. "Volatility Clustering and Scaling for Financial Time Series due to Attractor Bubbling". In: *Physical review letters* 89 (Nov. 2002), p. 158701. DOI: 10.1103/PhysRevLett.89.158701.

[7] Ray C. Fair. "The Effect of Economic Events on Votes for President". In: *The Review of Economics and Statistics* 60.2 (1978), pp. 159–173. ISSN: 00346535, 15309142. URL: http://www.jstor.org/stable/1924969 (visited on 12/13/2024).

[8] History, Art & Archives, U.S. House of Representatives. *Election Statistics: 1920 to Present*. https://history.house.gov/Institution/Election-Statistics/. (Visited on 12/14/2024).