Eidgenössische Technische Hochschule Zürich
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Complex Social Systems:
Modeling Agents, Learning and Games

Project Report

Network topology and monetary incentives drive establishment of conspiracy theories

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Contents

1 Abstract

Conspiracy theories have puzzled and divided many, and this for several centuries. However, today, in the midst of an era where information overflows, and almost anyone can forge an influential and powerful voice online through far-reaching mediums, conspiracy theories go more noticed than ever. In this work, we assess both, the effect of network topologies - representing different modes of social organization - and monetary incentives on the spread of conspiracy theories. We use agent-based modeling of conspiracies as social contagions with increasing levels of realism, ranging from a simple SIR model to an extension of the SEIZ modeling framework, where agents have attributes and can spend and earn money with conspiracies, called SEIZM model. We find that 1) conspiracies propagate faster if the network connectivity is high and 2) the introduction of a monetary incentive to solidify identification within groups of believers introduces a trade-off due to the possibly alienating effect of monetary suggestions. These results are largely robust for different model assumptions and parameter values. Our findings suggest that increased connectivity of a society in combination with monetary incentives could accelerate the spread of conspiracy theories.

2 Individual contributions

The overall project was achieved by a combination of research, model development, model implementation, and analysis.

The authors confirm their contributions to the presentation as follows: background on conspiracies and introduction: Jose Luis Ocana Pujol; presentation of the model: Gent Serifi; preliminary results: Anja Sjöström; outlook and future work: Chris Witzany.

The authors confirm their contribution to the project as follows: research on the dynamics of conspiracy theories: Jose Luis Ocana Pujol, Chris Witzany; development of a baseline model to study the dynamics of conspiracies: Chris Witzany; study and implementation of various network topologies: Jose Luis Ocana Pujol; development of the code library and framework: Gent Serifi; extension of the SEIZ model to SEIZ+ and implementation: Gent Serifi; extension and implementation of the model to include monetary incentives and extension of agent properties: Anja Sjöström; analysis and visualization of results: Gent Serifi, Anja Sjöström, Chris Witzany; All authors contributed to writing the final project report. All authors reviewed the results and approved the final version of the report.

3 Introduction

3.1 Conspiracy theories: a persisting phenomenon

Conspiracy theories have gained renewed attention in recent years by media (Guilhot and Moyn, 2020; Willingham, 2020; Stanton), institutions (European Comission, 2022; World Health Organization, 2020), and academia (Mahl et al., 2021; Leonard and Philippe, 2021; Douglas et al., 2017; van Prooijen and Douglas, 2017) alike. Contrary to what would seem given this renewed attention, conspiracy theories have really existed throughout history and come in a wider variety of forms (van Prooijen and Douglas, 2017; Mahl et al., 2021).

We define conspiracies as hypothesized explanations for events or actions that contradict conventional wisdom and instead relate to covert plans by influential people or institutions acting in their own self-interest (Mahl et al., 2021; Olshansky et al., 2020; Douglas et al., 2017; van Prooijen and Douglas, 2017). By applying these broad criteria, it is possible to classify a wide range of hypotheses as belonging to the family of conspiracy theories, from interpretations of historical and political events to alternative explanations of the natural world (Mahl et al., 2021).

3.2 A public perception-evidence gap?

Given this recent broad attention, one might be tempted to think that the belief in such theories has increased in recent years. In this context, the results of a variety of surveys have been taken by media as the proof of an increasing public willingness to believe in conspiracy theories. However, recent scholarly efforts to determine whether societal belief in conspiracy theories has increased over time have been inconclusive, leading to the claim that the belief in conspiracy theories may not have actually changed significantly over time, but rather has been subject to more attention (Uscinski et al., 2022).

Although that is a powerful hypothesis that has in turn received wide media attention (Stanton; Guilhot and Moyn, 2020; Willingham, 2020), one should point out that so far there is only one academic piece supporting this apparent gap between perception and reality (Uscinski et al., 2022). Additionally, the work by Uscinki et al. is mostly limited to the post social media age, which is problematic since the variety of conspiracy theories leads to a big range in the age of the theories themselves, ranging from theories that are a few years old, like recent theories surrounding COVID-19 and its origins, to theories that are centuries old (van Prooijen and Douglas, 2017; Uscinski et al., 2022).

In this regard, the Flat Earth theory is paradigmatic: it is currently the second most popular conspiracy theory on Twitter (Mahl et al., 2021) and has origins dating back to the nineteenth century. The doctrine, which was first associated with Bible literalism among British religious extremists, later spread to the United States, where the International Flat Earth Research Society was founded in the 1970s. Society was reborn in the early twenty-first century through the use of internet discussion forums, which led to the creation of a website in 2009 (Olshansky et al., 2020). The presence on YouTube, which has been identified as the key driver of Flat Earth knowledge, only developed in the early 2010s (Paolillo, 2018), and Flat Earth conferences, in which believers gather and frequently sell various items, have only recently emerged (Olshansky et al., 2020).

3.3 The money question

The increase of Flat Earth believers on YouTube resulted in especially vocal Flat Earth personalities becoming representatives of the movement with massive audiences (Mahl et al., 2021). For the Flat Earth influencers, their audience can become very lucrative, as potential buyers of merchandise or for targeted advertisements. These monetary incentives are evident for the organizers and entrepreneurs of Flat Earth conferences, who make money by selling tickets (priced from 200$ to 400$) and Flat Earth related items, respectively (Olshansky et al., 2020). Another prolific example of making a profit with conspiracy theories is Alex Jones, infamous for denying the shooting at Sandy Hook elementary school in 2012, who build an audience by peddling conspiracies and made over a hundred million dollars by selling survival gear, nutritional supplements, and merchandise of his show "Infowars" (Hsu, 2022). The monetary incentives to spread conspiracies are apparent, but what about the effect of being asked "to buy into" a conspiracy theory?

Many Flat Earth believers invest in the conspiracy by buying merchandise. They demonstrate their beliefs by wearing Flat Earth T-shirts, putting Flat Earth stickers on their cars, or buying models depicting a Flat Earth (Olshansky et al., 2020). Such behavior demonstrates membership status (Snow and Machalek, 1984) and can accelerate the consolidation of a believer's identity as a member of the group, i.e. Flat Earthers (Leverso and Matsueda, 2019; Phelan and Hunt, 1998; Stanfill and Condis, 2014), thereby inhibiting future opinion change, since the opinion "that the earth is flat" it is deeply tied to their identity (Nyhan and Reifler, 2019). Therefore, monetary transactions could both facilitate the spread of a conspiracy as well as make reversion of belief less likely.

3.4 Aims

This gap in the literature offers a chance to investigate why and how conspiracy beliefs, such as Flat Earth, have spread through different societies, and why there is a widespread cultural belief in their relevance. In this study, we will address the following question:

RQ1. **What are the factors that lead to the propagation of conspiracy theories in societies with different degrees of connectivity?**

This will be addressed by combining two hypotheses:

Hypothesis 1 (H1): *Different network topologies lead to different dynamics of opinion change propagation.*

Hypothesis 2 (H2): *Monetary incentives facilitate the spread of minority opinions*

4 Description of the Model

4.1 Epidiemological Agent-Based Modelling to study opinion change

Ultimately, a single person or a small group of people come up with a conspiracy theory and pass it on to others, who - if they end up believing the conspiracy - then further propagate it to other unknowing individuals. In this sense, conspiracy theories, rumors, or information, in general, are very similar to infectious diseases. Hence, it does not come as a surprise that modeling of such social contagions has been heavily inspired and influenced by epidemiological population models (Zhao et al., 2013; Xiong et al., 2012; Daley and Kendall, 1965; Rapoport, 1953). The most famous and fundamental model of this sort is the SIR model, which originally describes the population dynamics of Susceptible (S), Infected (I), and Resistant (or Recovered, R). Susceptibles can get "infected" with new information, e.g. a conspiracy, by rate α upon contact with an Infected, which already believes the new conspiracy, or Recover/become Resistant, here with the rate $1 - \alpha$, i.e. they disagree with the conspiracy.

4.2 The SEIZ model

Many epidemiological models have expanded upon the SIR framework to capture the more nuanced differences between the spread of infectious diseases and the spread of information on social media (Zhao et al., 2013; Xiong et al., 2012). One of those is the SEIZ population model (Bettencourt et al., 2006), which has been shown to accurately capture the spread of rumors and news on Twitter (Jin et al., 2013). As in epidemiological models, each letter represents a sub-population of individuals: S stands for Susceptible (i.e., have never heard the rumor), E for Exposed (i.e., have heard the rumor), I for Infected (i.e, believe the rumor and propagate it), and Z stands for Skeptic (i.e. don't believe the rumor and don't propagate it). Individuals change their state of belief and thereby sub-population by interacting with each other. After coming into contact with an infected individual a susceptible turns infected with rate β or becomes exposed with rate 1-β. Similarly, a susceptible that interacts with a skeptic individual turns either skeptic or exposed with rate γ or 1-γ, respectively. Exposed turn infected upon contact with infected individuals with the same rate as susceptibles β, however, they also turn infected with the rate ϵ independent of contact with other individuals. This delay in turning infected represents the internal processing of an individual after learning new information. Contact between infected and skeptic individuals has no effect. See Figure 1a for an overview of the transitions between the possible states of the individuals.

The original SEIZ population model consists of ordinary differential equations, one for each sub-population representing one state of belief (Bettencourt et al., 2006) and assumes homogeneous mixing between the populations, i.e. interactions between individuals are completely random (Keeling and Rohani, 2008). However, in reality, interactions are highly structured due to existing social relations between the individuals (Aleta et al.,

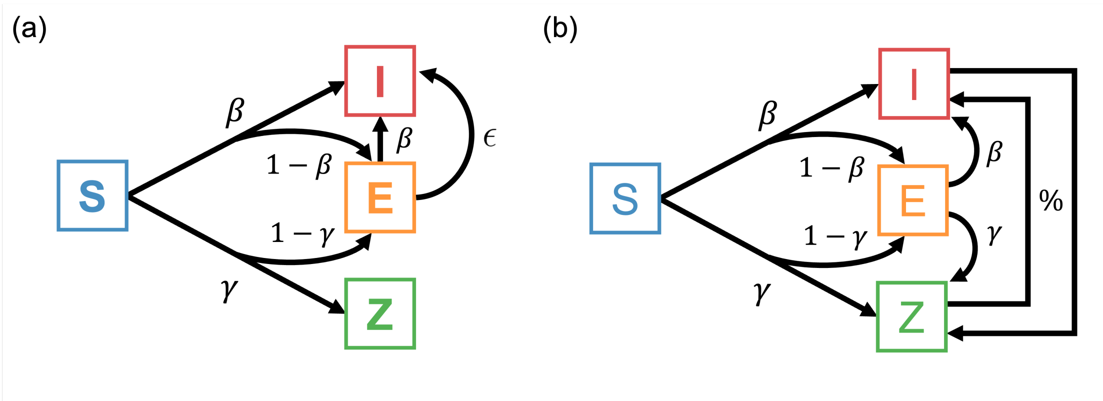

Figure 1: **Visualisation of the possible transitions between belief states in the (a) SEIZ model and (b) SEIZ+ model.** In both models there are four possible belief states: Susceptible (S), Exposed (E), Infected (I), and Skeptic (S). Susceptible Individuals stochastically change their state after interaction with Infected or Skeptic individuals, with probabilities β and γ, to either Infected or Skeptic, respectively. In case a Susceptible individual does not change to Infected/Skeptic, i.e with probabilities $1 - \beta/1 - \gamma$, they change to the Exposed state. In the SIZE model (a) Exposed, like Susceptibles, also stochastically change their opinion after interaction with Infected. In contrast, in the SEIZ+ model (b) Exposed individuals can at every time step stochastically transition Believe state to either Infected or Skeptic, with probabilities β and γ, as long as their interacting neighbor is not of the opposite opinion. Exclusively in the SEIZ+ model (b), Infected can change state to Skeptic, and vice versa, if more than a certain threshold % of their neighbors are of the opposite belief state.

2020). Therefore, we here implement the SEIZ model as a stochastic agent-based network model. Every agent is represented as a node in a network (see topology figure) and can have one of the four possible belief states defined in the SEIZ model (see Figure 1a). The major difference between our network model and the original population model is, that at every time step, every agent only interacts with one random neighbor, instead of equal probabilities of interaction between all agents. The conditions for state changes between interacting agents are unchanged from the original SEIZ model (described above, see Figure 1a). However, in our agent-based model state changes are stochastic and occur with probabilities corresponding to the rates described above.

4.3 Limitations of the SEIZ model

While the SEIZ modeling framework has been shown to be applicable to the spread of news and rumors on Twitter (Jin et al., 2013), it does have some major simplifying assumptions. For instance, infected individuals, i.e. believers of the conspiracy theory, can never transition to any other state, i.e. stop believing. Similarly, skeptics can also never change their state. Furthermore, due to the delayed transition to infected (ϵ) every exposed individual, will turn infected over a long enough time frame - even in the absence of a second interaction with an infected. This is not realistic, as after exposure to a conspiracy theory, over the course of thinking and processing the new information, one could also come to the conclusion not to believe and become skeptic instead. This is especially relevant in the context of conspiracy theories, such as Flat Earth, where abundant data debunking the conspiracy is accessible. Lastly, the interaction of exposed individuals with skeptics cannot affect their belief state, while interactions with infected can, even though interactions between susceptibles and skeptics can.

4.4 SEIZ+ model

To remedy these simplifications we expand upon the SEIZ model and create a SEIZ+ model (see Figure 1b). We enable, Exposed to stochastically transition to either Skeptic or Infected, with probabilities β and γ, as long as their interacting neighbor is not of the opposite opinion. Thereby, Exposed can change their opinion change even though, they interact with a Susceptible neighbor, which more accurately represents internal opinion formation. Lastly, we add a community-level effect on opinion change (depicted with %), this represents a threshold value of how many of the neighbors of a skeptic agent need to be infected for them to change to infected, and vice versa.

4.4.1 The addition of a monetary incentive

In order to model monetary incentives to our system we need to complexify agent properties and let them dictate interactions and transitions alongside the stochastic element. We, therefore, introduced four new agent properties in what we call the SEIZM model. They are the following:

(I) Certainty - a floating point between 0 and 1

(II) Influence - a floating point between 0 and 1

(III) Money - an integer whose sign represents the bank balance of the agent and whose absolute value represents the number of transactions

(IV) Sentiment - a floating point between 0 and 1

The first attribute - certainty - describes how certain an agent is in his opinion. Briefly, the higher the certainty of an agent, the more convincing an interacting agent needs to be to move him toward his opinion.

The second attribute - influence - describes how convincing an agent is. The intuition is to model the behavior of "influencers" and community leaders. In particular, we develop a relationship between the money an agent has and his influence.

The third attribute - money - enables agents who are Infected to, provided they meet a certain influence threshold and certainty threshold, ask any other Infected or Exposed agent to spend money on them with a certain probability. In the subsequent interactions, agents who have spent or made money on the topic of conspiracies will then have a higher certainty and their belief more ingrained in their identity.

Finally, the last attribute - sentiment - is one used by agents in the Exposed state to describe to which opinion - Infected or Skeptical - they tend. It plays a role in their interactions with Infected or Skeptical agents and, loosely, determines how likely they are to switch their opinion.

Concerning the interactions between agents, eight of them are specified and they depend on the parameters of each agent. They are based on the following descriptions:

- Susceptible with Exposed: Susceptible transitions to Exposed
- Exposed with Skeptic / Infected: If the Exposed agent has a sentiment between 0 and 0.5 / 0.5 and 1 (i.e. tends towards the Skeptics / Infected) then if the Skeptic / Infected is more certain than the Exposed and influential enough the Exposed directly transitions to Skeptic / Infected. This increases the influence of the Skeptic / Infected by how close the Exposed's sentiment was already to 0 / 1 (i.e. less increase if was already close to 0 / 1) and increases the certainty of the Exposed agent by a factor of the Skeptic's / Infected's influence. However, if the Skeptic / Infected is not influential enough or the Exposed is more certain than him then the Exposed simply adapts his sentiment to approach 0 / 1 but remains in the Exposed state.

  On the other hand, if the Exposed has a sentiment that is opposite to that of the Skeptic / Infected then if the Skeptic / Infected is influential enough they will still try to convince the Exposed. In the case they are successful (determined by a random variable being inferior to their influence - the higher the better chances) the Exposed transitions to Skeptic / Infected and the influence of the Skeptic / Infected is increased by a factor of how far the Exposed's sentiment diverged from them. However, should the attempt be unsuccessful, this will alienate the Exposed whose sentiment will move in the opposite direction and whose certainty will increase. Furthermore, the Skeptic's / Infected's influence will decrease.
- Additional monetary interaction for Exposed with Infected: In the case where the Infected's certainty and influence are above the "certainty_threshold" and the "influence_threshold" parameters, and if the infected has never spent money (is in a position of superiority), moderated by an additional random component, the interac-

tion described in the point above does not occur but instead the Infected will suggest to the Exposed to spend money on the cause. There are two cases: the Exposed either agrees or disagrees:

1. The Exposed agrees if they have a matching sentiment, a low influence, and a high certainty. This triggers a transition to the Infected state. It also causes the influence of the Infected to increase as well as an increase of the certainty of the Exposed (adhering to this idea of rooting the conspiracy into your identity if you spend money on it)
2. The Exposed disagreed otherwise. This has for consequence to decrease the Infected's influence as well as decreasing the sentiment of the exposed (pushing him toward the skeptics).

- Susceptible with Skeptic / Infected: The susceptible agent will directly transition to Skeptic / Infected state with probability *prob_S_with_Z* / *prob_S_with_I* which will increase the Skeptic's / Infected's influence. Otherwise, the Susceptible agent will move to Exposed and will be attributed a sentiment close to 0 / 1 the more influent the Skeptic / Infected is. If the Skeptic / Infected is influent enough the certainty of the Susceptible will also increase and the influence of the Skeptic / Infected will increase.
- Skeptic with Infected: The agent with the stronger influence of the two will make the other agent transition to Exposed if he also has a stronger certainty or will simply reduce the other agent's certainty by a factor of its own influence if the other agent has the highest certainty.
- Skeptic with Skeptic: We adapt the certainty of both agents as follows

$$\frac{1 + \text{certainty}_1 + \text{certainty}_2}{3}.$$

  Both agents reinforce their own certainty.
- Infected with Infected: In this interaction, a monetary suggestion occurs whenever one or both agents satisfy the certainty, money, and influence threshold condition. The other agent agrees if he has a low influence (i.e. easily influenced) and has a negative or null balance (i.e. is not a competitor since has never made money) and disagrees otherwise. If he agrees the transaction is performed, the certainty of the spender is increased (adhering to this idea of rooting the conspiracy into your identity if you spend money on it) and the influence of the receiver is increased. If he disagrees the influence of the spender is increased and the influence of the receiver is decreased the lower the spender's influence was (adhering to the idea that an agent with a lower influence should be easier to convince).

5 Implementation

5.1 Network topologies

The models were tested on four different network topologies chosen from the graph generator library of NETWORK X (Hagberg et al., 2008). The graphs were chosen to distribute nodes in four different ways, each of which represents a different mode of social organization. The four chosen graphs were the Caveman (Connected Caveman)Watts (1999), the Windmill, the Small World (Newman Watts Strotgatz)Newman and Watts (1999), and the Dual Barabasi (Dual Barabassi-Alberts)Moshiri (2018).

To establish that any discrepancies in the dynamics and ultimate output of the models are attributable to the network topology and not to other differences, the four networks are computed to contain the same number of agents (nodes, n) and the density, as defined in Equation 1.

$$d = \frac{2m}{n(n-1)} \tag{1}$$

Where n and m are the number of nodes and the number of edges, respectively. By forcing a constant density across networks we assume that the number of connections of any sort that a human individual may have remains constant throughout civilizations and historical times. This assumption is based on the research tradition established and popularized by Prof. Dunbar and his colleagues (Dunbar, 1993).
The four networks differ under different metrics, most notably the degree distribution, that is, to how many edges each node in the graph is connected. Figure 2 depicts an example of each of the four network topologies with $n = 240$ as well as the resultant degree distribution of the various nodes. One way of reducing the degree distribution to a single number is to use the clustering coefficient:

$$cc = \frac{1}{n} \sum^{n} \frac{2T(u)}{deg(u)(deg(u) - 1)} \tag{2}$$

Where $T(u)$ is the number of triangles of a given node u, $deg(u)$ indicates the degree of a node. We implemented some functions to ensure finding the appropriate parameters for a given d and n. The functionality (available as $functions_networks$) can be explored on the notebook $network_parameters_120$. To show the tolerance of this function, Table 1 shows the density and the clustering coefficient of 4 generated graphs with $n = 780$ and an objective density of $d = 0.15$. We argue that the four chosen networks represent four historical modes of societal organization. The caveman model is the most sparse map possibleWatts (1999) and we consider it a good representation of communication in early human history. It is characterized by quite equal degree distribution, as shown in Figure 2 (a). The addition of a central node leads to the windmill network, which therefore has

Graph name	Density	Clustering coefficient
Caveman	16.55	99.96
Windmill	16.78	99.88
Small world	16.69	64.54
Barabassi	14.50	47.95

Table 1: Density and clustering coefficient of 4 generated graphs with $n = 780$.

a very unequal degree distribution. The central node could be understood as centralized political power but also as legacy media. To represent the modern internet we use two random network topologies with fairly different degree distributions as shown in 2 (c) and (d). The chosen small world network is characterized by very short distance between nodes and by allowing to change the *cc* just by tuning the probability of reconnectionNewman and Watts (1999). The Dual Barabasi network was chosen since it leads to a dual distribution of connections, in line with the data about modern social networksMoshiri (2018). Table A.2 shows the arguments of all the network parameters used in this project.

5.2 Models

All described models (SIR, SEIZ, SEIZ+ and SEIZM) are implemented in the open-source agent-based modeling framework Mesa (Kazil et al., 2020). Figures were made using the python framework plotnine, which is based on ggplot (Kibirige et al., 2022). All code related to the model and figures is publically available on GitHub (`https://github.com/ChrisWitzany/opinion_network_model`).

6 Simulation Results and Discussion

6.1 Results

Over the last decades, conspiracies have gained increased media attention. However, whether believers in conspiracy theories have actually increased in frequency remains an open question. Here, we use agent-based modeling to investigate, whether changes in network topology and the rise of monetary incentives to spread conspiracy, could explain an increase in believers.

6.1.1 The topology effect on propagation speed

To assess the effect of network topology on the spread of conspiracy theories, we define four topologies: Caveman, Windmill, Smallworld and Dual Barabasi, which as discussed earlier intend to represent different societal organizations. For each of these networks, we simulate the spread of a conspiracy theory originating from a single person, by agent-based

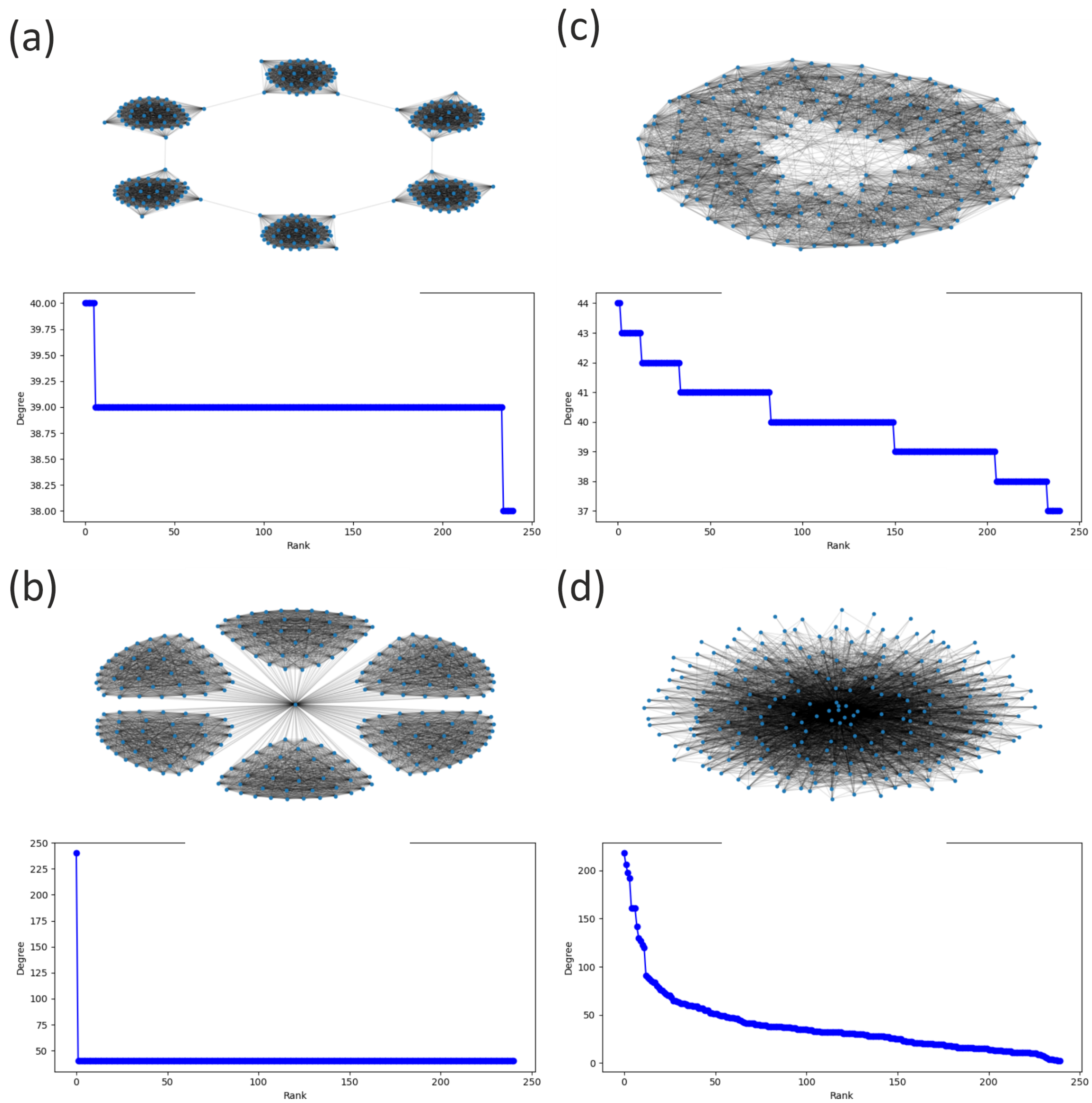

Figure 2: **Examples of the different network topologies used in this project.** (a): Caveman topology. Characterized by k cliques of l nodes. Each clique has a single edge that is rewired to a node in the clique next to it. (b): Windmill. Characterized by k cliques of l nodes joined at one central node. (c): Small world topology. Graph formed by a ring of n nodes. Posteriorly, each ring node is linked to its k closest neighbors. Finally, shortcuts are built by adding new edges as follows: for each edge of the ring with k nearest neighbors, a new edge is added with a randomly selected existing node with a probability of p. (d): Dual Barabasi topology. In this graph, the network is expanded by adding new nodes that are preferentially associated to high degree nodes that already exist and have edges k (with probability p) or l (with probability *(p-1)*).

modelling with four different kinds of models of increasing complexity: SIR, SEIZ, SEIZ+ and SEIZM (see Description of the Models section for details). This way we can assess the robustness of our results in regard to our underlying model assumptions of opinion spread. All the simulations in this subsection were done using PAR100 (see A.2.

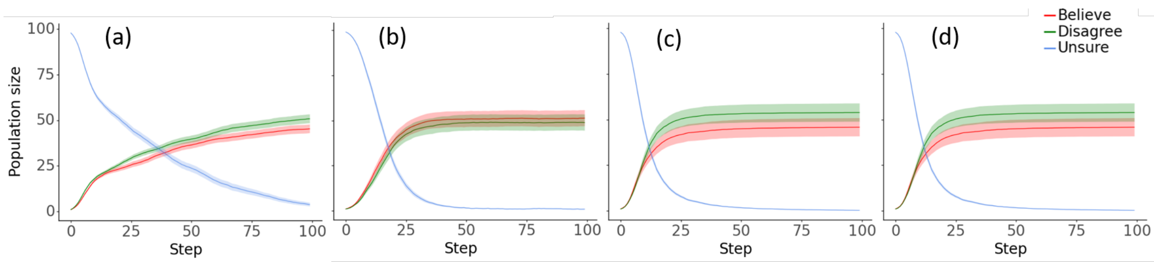

Figure 3: **SIR model dynamics of conspiracy spread for four different topologies.** Shown are the mean number of Infected (Believers, red line), Resistant (Disagree, green), and Susceptible (Unsure, blue) for 100 model runs over time (Steps) for Caveman (a), Windmill (b), Smallworld (c), and Dual Barabasi (d) topologies. Error bars show standard errors of the mean. Starting conditions are 100 agents, with one Infected and one Skeptic. Probability of opinion change α from Unsure to either Infected or Skeptic after the interaction is 0.03.

The SIR model is the simplest model, allowing only for three opinion states: Unsure (corresponds to Susceptible), Believe (Infected) and Disagree (Resistant/Recovered) with the conspiracy. Our simulations show that for this simple model, the final states for all four network parameters are largely comparable, with close to 50% Believers and 50% agents that disagree at the end of simulations (Figure 3). However, the dynamics until a steady state is reached differ between the networks, with Caveman being the slowest and Dual Barabasi the fastest.

The final stages generated by the SEIZ model, show that for all four networks about $80-90\%$ of the population end up being Infected and only about $10-20\%$ as Skeptic. This substantial difference in end states between SIR and SEIZ model arises due to the inclusion of the Exposed opinion state in the SEIZ model, which are Susceptibles that had contact with either an Infected or a Skeptic and over time transition to Infected with a rate ϵ (see figure 1a). However, the trajectories of the SEIZ model, similar to the SIR model results, show that final plateaus are reached with increasing speeds from the Caveman to the Dual Barabasi network topologies. The dynamics of the Exposed mirror the differences in propagation speed, showing increasingly steep curves with increasing maximal numbers of Exposed. Interestingly, for the Windmill topology (Figure 4b) the time point when the conspiracy passes the central node can be seen as the beginning of the second phase of the biphasic increase of the Exposed agents.

To more realistically simulate the spread of conspiracy theories, we here develop an

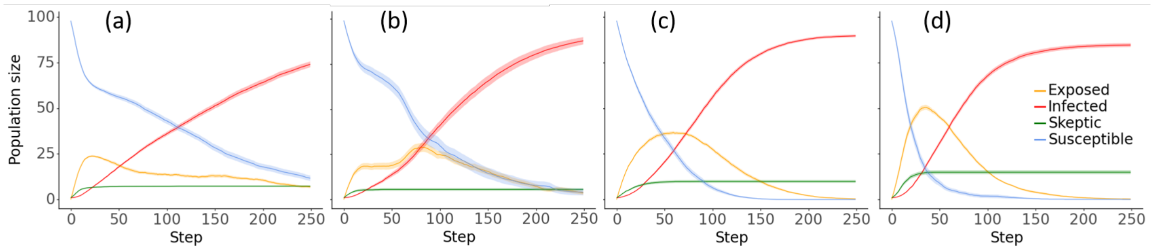

Figure 4: **SEIZ model dynamics of conspiracy spread for four different topologies.** Shown is the mean number of Exposed (orange line), Infected (red), Skeptic (green), and Susceptible (blue) for 100 model runs over time (Steps) for Caveman (a), Windmill (b), Smallworld (c), and Dual Barabasi (d) topologies. Error bars show standard errors. Starting conditions are 100 agents, with one Infected and one Skeptic, and all others Susceptible. The model parameters were, $\beta = 0.3, \gamma = 0.3$ and $\epsilon = 0.01$. See Figure 1 and the SEIZ model description for details.

expansion of the SEIZ model, called SEIZ+, in which Exposed can stochastically transition to Skeptic or Infected, instead of exclusively to Infected. Further, we add that Skeptic and Infected can convert if more than % of their neighbors are of the opposite opinion (Figure 1b and Model Description). Our simulation results, show that the possibility of Exposed to transition to Skeptic recovers the end states observed for the SIR model, with 50% of the agents being Skeptic and 50% being Infected. However, this only holds if $\gamma = \beta$. Otherwise, the dominant population corresponds to the larger transition probability (See figure 7 and figures A.1 and A.2 for dynamics). In the same way as for the SIR and the SEIZ trajectories, the more connected the network is, the faster the steady states are reached.

Trajectories of opinion spread for the SEIZM model reveal a stark difference in end states between Caveman and the other three topologies (6). In the Caveman topology, the final dominating opinion is Susceptible with about 40%, followed by Skeptics (30%), Infected (20%)and lastly Exposed (10%). In contrast, in the other three topologies the Skeptics dominate with > 60% of total agents with around 25% Infected, and few Susceptible and Exposed. This dominance of agents never exposed to the conspiracy is unique to the Caveman SEIZM (see Figures 3, 4, **??**). Further, only for the SEIZM model are all opinion states present at the end of the simulation, however the higher the connectivity of the topology the bigger the size differences. Interestingly, our finding, that the speed until steady state is reached shortens with higher connectivity holds also for the SEIZM model, with the Dual Barabasi network reaching steady state fastest and Caveman slowest.

In summary, we find that the propagation speed of conspiracy theories is dependent on the network topolog, confirming hypothesis 1. The caveman network is always the slowest

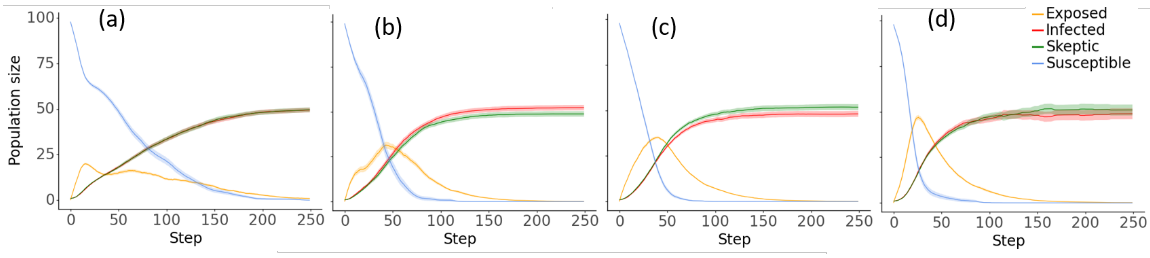

Figure 5: **SEIZ+ model dynamics of conspiracy spread for four different topologies.** Shown is the mean number of Exposed (orange line), Infected (red), Skeptic (green), and Susceptible (blue) for 100 model runs over time (Steps) for Caveman (a), Windmill (b), Smallworld (c), and Dual Barabasi (d) topologies. Error bars show standard errors. The starting conditions are 100 agents, with one Infected and one Skeptic, and all others Susceptible. Model parameters are $\beta = 0.3, \gamma = 0.03$ and $\% = 0.7$. See Figure 1 and the SEIZ model description for details.

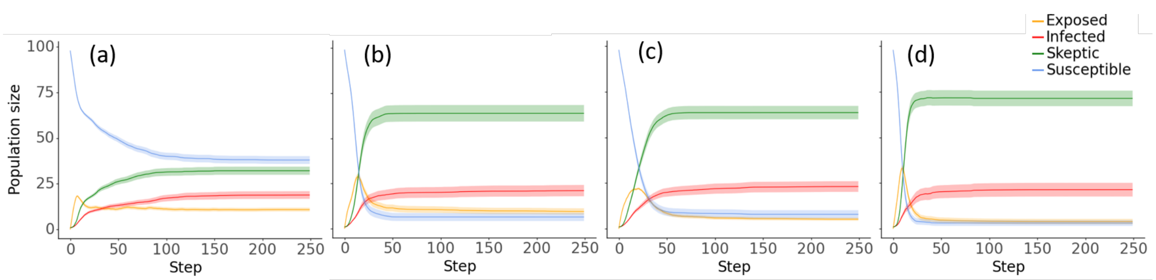

Figure 6: **SEIZM model dynamics of conspiracy spread for four different topologies.** Shown is the mean number of Exposed (orange line), Infected (red), Skeptic (green), and Susceptible (blue) agents for 100 model runs over time (Steps) for Caveman (a), Windmill (b), Smallworld (c), and Dual Barabasi (d) topologies. The starting population consists of 100 agents, of which one is Infected (i.e. believes the conspiracy) and one is Skeptic (i.e. disagrees with the conspiracy), all others are Susceptible (i.e. have never heard of the conspiracy). Model parameters are $\beta = 0.03, \gamma = 0.03, \% = 0.7$, $certainty\ threshold = 0.3$, $influence\ threshold = 0.3$, $money\ threshold = 0.3$, $influence\ increase = 0.1$, and $certainty\ increase = 0.1$. Error bars show standard errors. See SEIZM model section for details on the parameters.

one to propagate, most often followed by the windmill. This happens despite the fact that both early history networks have the same clustering coefficient (1). This shows that the clustering coefficient does not capture the connectivity of a network well Watts (1999). The two topologies chosen to represent the internet lead to faster communication. These findings are robust for all tested models (figure 3, figure 4, figure, and figure 5, figure 6). The results also hold when the models are tested under 5 different network parameters (Table A.1).

6.1.2 The topology effect on minority opinions

To test whether the topology also has an effect on the final state of a simulation, independently from the speed at which this state was reached, the phase diagrams were calculated for 200 steps, a number higher than it takes any topology to reach equilibrium in the SEIZ+ model as shown in Figures 3,4 and 5. As discussed in Section5, the SEIZ+ model is characterized by three parameters: β, γ and %. Therefore, in order to obtain sensible phase diagrams, the non-iterating parameter needs to be kept at a reasonable number.

Figure 7 shows the phase diagrams by varying the two probabilities of the model, γ vs β. As expected, the results show that higher β lead to a final believer population, while higher γ lead to final non-believer populations. However, the results show no clear topological difference. To ensure that this lack of topological dependence is not given by the chosen network parameters, the phase diagrams were produced for a set of five different network parameters for the same number of nodes (see A.2). Figure A.3 shows this sensibility analysis and how varying the network parameters does not lead to an increase in the topological dependence.

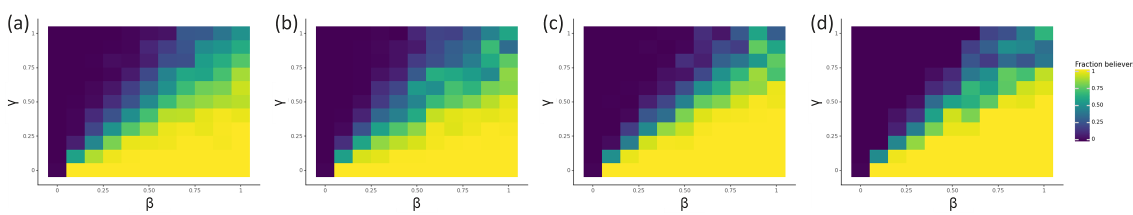

Figure 7: **Influence of γ vs $beta$ on the final number of believer for SEIZ+ model with parameters param2.** Shown are the phase diagrams for (a) Caveman topology, (b) Windmill topology, (c) Small world topology, and (d) Dual Barabasi topology. Neighbor threshold % is kept constant at 0.7 for all topologies.

The introduction of the neighbour threshold % in the phase diagrams leads to topological dependencies. Figure 9 shows that the effect of % on the final output of a simulation depends greatly on the network topology: while in (a) and (b) there are virtually no believers in the simulations with a neighbor threshold higher than 0.05, almost independently from the probability of γ, in (c) and (d) there are believers as long as γ is small. A more

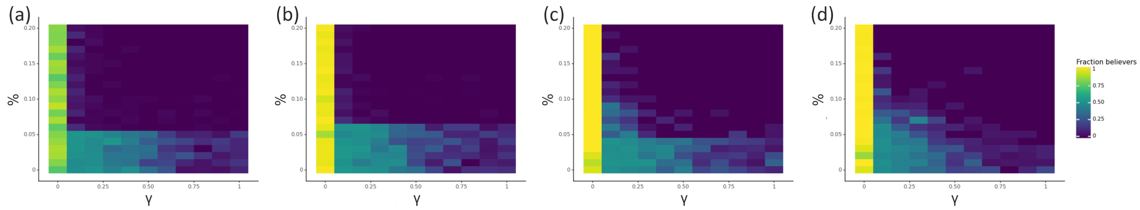

Figure 8: **Influence of γ vs neighbor threshold % on endstates of the SEIZ+ model. vs neighbour param2 SEIZ+.** Shown are (a) Caveman, (b), Windmill, (c) Small world, and (d) Dual Barabasi topology. % has less influence on the final fraction of believers in topologies representative representing modern social organization.

visual description is that while (a) and (b) are dominated by a horizontal cut-off, (c) and (d) are not. This result holds for the sensitivity analysis with different network parameters, as shown in figure A.4. It should be noted that the complementary phase diagrams, i.e. with β instead of γ, also show the same results, as shown in Figure A.5.

We can therefore conclude that in the more connected networks representing the Internet (Smallworld and Dual Barabasi) peer pressure has a smaller effect than in the less connected networks (Caveman and Windmill), which represent pre-internet societies. Since these two last networks also have lower clustering coefficients (see table 1), this indicates that the more concentrated your neighbors are, the less peer pressure you need to align your opinion with the majority opinion around you.

6.1.3 The effect of money spread in topology

The results of the SEIZM model when varying the *moneythreshold* parameter (Figure 9 show that the higher the *moneythreshold* the fewer people will propose monetary transactions, and suggest a more complex answer to hypothesis 2: a trade-off between the incentive to make money and risking alienation by asking for investments. This trade-off shows in all network topologies 9: the higher the probability to become a believer β, the lower the *monetarythreshold* needs to be to generate a high fraction of believers at the end of the simulation (200 steps).

In other words, we notice that the *moneythreshold* does have an impact on the number of believers since the separation hints at a negative slope and not a vertical line. However, the results do not suggest that more monetary interaction makes it more favorable to the development of a believer community. Indeed we notice that the higher the money threshold - i.e. the less the people ask for money - the easier it is to get to a believer state or in other words, the conventional way of becoming a believer is more efficient. This may be explained by the possible deterrent effect when an agent refuses the monetary interaction and moves away from the believer community.

As to network topologies, we observe that believers develop or survive better, for the

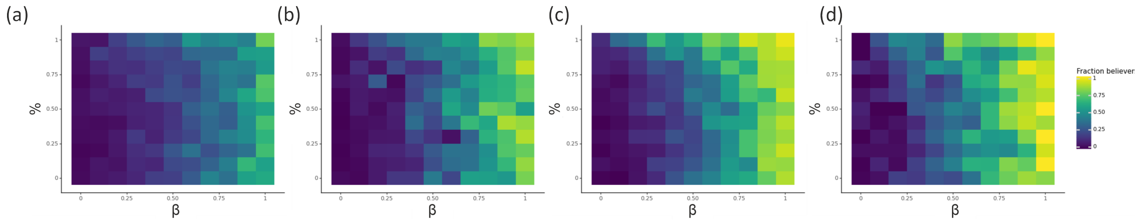

Figure 9: **Interplay of β and $moneythreshold$ % on end states of the SEIZM model.** Shown are (a) Caveman, (b), Windmill, (c) Small world, and (d) Dual Barabasi topology. An increase in β leads to a smaller increase in the percentage of believers in Caveman and Windmill. Other model parameters used are $\gamma = 0.03, \% = 0.8$, $certainty\ threshold = 0.3$, $influence\ threshold = 0.3$, $influence\ increase = 0.2$, and $certainty\ increase = 0.2$. See SEIZM model section for details on the parameters.

same set of parameters, in topologies representing more modern social network eras (Small world and even more so Barabasi).

This leads us to the conclusion that although monetary incentives introduce new interesting dynamics, network topology remains a better quantifier of misinformation spread with the current set of parameters that describes our societies.

7 Discussion and Outlook

7.1 Discussion

We find that with increasing network connectivity, i.e. from Caveman to Dual Barabasi, steady states are reached faster for all our models (Figure 3, 4, 5, 6). This finding is in line with previous work, which shows that highly connected networks facilitate the spread of minority opinions, such as conspiracy theories (Alvarez-Galvez, 2016). In general, network topology is known to affect spreading dynamics, both those of information as well as of infectious diseases (Ganesh et al., 2005; Saxena et al., 2015; Delre et al., 2010), especially in static networks (Keeling, 1999; Eames, 2008). However, our findings show that conspiracy theories are only inhibited by small cliques with high inter-connectivity (i.e. Caveman topology), whereas infectious diseases die out because they kill their hosts faster than they can spread (Keeling, 1999). Further, we find that for the SEIZ+ model the effect of the neighbor threshold % is dependent on network topology 9. For Small world and Dual Barabasi topologies, higher threshold values result in higher fractions of believers present at the end of simulations than for the Caveman and Windmill networks. Intuitively, agents in less connected networks, such as the Caveman topology, experience higher peer pressure due to isolated, intra-connected cliques of neighbors. Interestingly, Wu et al. report similar findings for an agent-based implementation of the Spiral of Silence opinion model. They report that the connectivity between cliques can lead to a global convergence of opinions

(Wu et al., 2015), if agent activation is uniform (Cabrera et al., 2021), which is the case for our model. Consistency between these findings is not intuitive as The Spiral of Silence and epidemiologically inspired models of opinion spread differ fundamentally and makes further comparisons far-stretched. However, we are not aware of any comparable models of social contagion model that incorporate neighborhood effects on networks.

The effects of monetary transactions on the spread of opinions are mainly studied in the context of advertising López et al. (2021) or investments Chen et al. (2019). Even though, their influence is also apparent in the spread of conspiracies Olshansky et al. (2020). Here, we develop a SEIZM model, which includes monetary incentives and deterrents into a SEIZ model (see Model descriptions for details). Our results show a trade-off between spreading the conspiracy and making money, i.e. we do not observe a substantial increase in believer frequency compared to the SEIZ+ model with comparable parameters. This can be explained by the fact that although monetary incentive does solidify certainty in beliefs, these beliefs must first be acquired, which the monetary incentive makes much more difficult due to possibly alienating an agent if he rejects the proposal to invest. In conclusion, our results suggest that the introduction of a monetary incentive can create a very volatile environment where a solidification behavior is only observed if an appropriate environment for belief adoption is created.

7.2 Outlook

For our models, we assume at baseline that neighbor interactions can happen both ways, i.e. either agent can initiate contact. However, in reality, many networks display uni-directional connections, which means only one agent can initiate interactions with the other. This is especially true for modern-day social media networks, where initiating an interaction with an influencer is very unlikely. We try to address this limitation in our SEIZM model, where interactions cannot result in opinion change if the agents' influence and certainty values differ greatly (see SEIZM Model description). However, previous work has shown that even if the overall network structure remains unchanged, switching from bi-directional to uni-directional interactions can generate substantially different outcomes of final opinion states (Gandica et al., 2010). Future research is required to investigate how opinion spread in differently connected networks is impacted by changing from bi-directional to uni-directional interactions.

One caveat of our sensitivity analysis is that we only vary parameters pairwise. This does not pose a serious problem for the SEIZ and SEIZ+ models, however for the SEIZM model, which has 8 variable parameters, which could have different effects depending on the values of the others. To address this one could systematically sample the 8-dimensional parameter space and utilize a dimension reduction technique, such as a Linear Discriminant Analysis (Xanthopoulos et al., 2013), to assess which parameters have the most influence on the final opinion states. However, due to time constraints, this was beyond the scope of this work.

Lastly, we want to note that our modeling results could suggest that the effect of monetary incentives of opinion spread could be more positive if people are more likely to respond favorably to proposals of investing money into the conspiracy. However, other societal factors, confound this notion, as conspiracies are often associated with societal or financial crisis (Douglas et al., 2017; van Prooijen and Douglas, 2017). Therefore, it would be interesting to investigate different likelihoods of spending money, both in times of prosperity and crisis by introducing global sentiments, which influence agent behaviour and thereby more closely model the complexity of societies.

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Appendix A Supplemental Figures

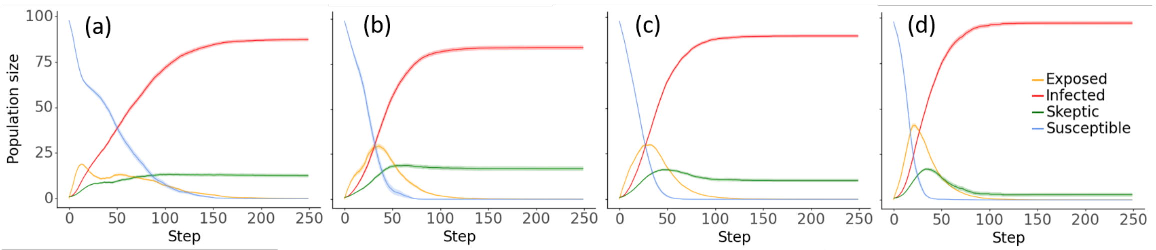

Figure A.1: **Endstate of SEIZ+ model dynamics is determined by β to γ ratio.** The dominant opinion is determined by which probability of opinion change is greater β or γ. Here, $\beta = 2\gamma = 0.06$, all other parameters as in figure 5. See figure A.2 for $\beta > \gamma$.

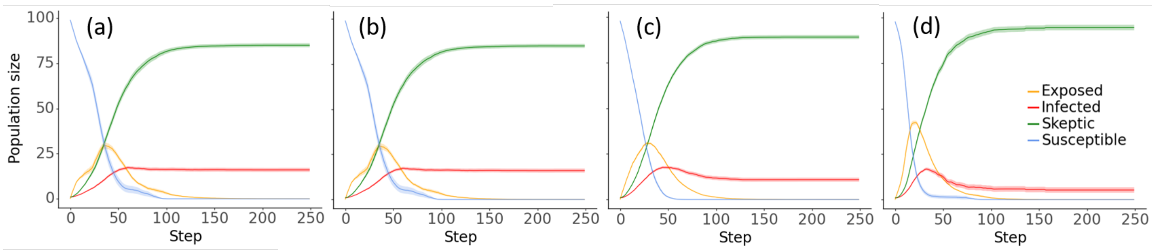

Figure A.2: **Endstate of SEIZ+ model dynamics is determined by β to γ ratio.** If $\gamma > \beta$, then Skeptic is the dominant opinion at simulation end ($\gamma = 2\beta = 0.06$, other parameters as in figure 5). See figure A.1 for $\gamma > \beta$.

		Caveman	Windmill	Small World	Dual Barabasi
SIR	P1	4	3	2	1
SIR	P2	4	3	2	1
SIR	P3	4	3	1	2
SIR	P4	4	1	3	2
SIR	P5	4	2	4	3
SEIZ	P1	4	3	2	1
SEIZ	P2	4	3	1	2
SEIZ	P3	4	3	1	2
SEIZ	P4	4	3	1	2
SEIZ	P5	4	3	1	2
SEIZ+	P1	4	3	2	1
SEIZ+	P2	4	3	1	2
SEIZ+	P3	4	3	1	2
SEIZ+	P4	4	3	2	1
SEIZ+	P5	4	3	1	2

Table A.1: Ordinal classification of how fast a topology reaches a static behaviour, where 1 is the fastest and 4 the slowest, for 3 different models and 5 different network topologies. The model parameters were kept the same as in the results section.

	Caveman	Windmill	Small World	Dual Barabasi
Par100	(5,20)	(10,11)	(100,10,0.05)	(100,12,50,0.95)
P1	(6,20)	(8,16)	(120,20,0)	(120,15,60,0.96)
P2	(6,20)	(8,16)	(120,20,0.05)	(120,21,84,0.96)
P3	(6,20)	(8,16)	(120,20,0.1)	(120,27,108,0)
P4	(3,40)	(3,41)	(120,40,0)	(120,15,60,0.6)
P5	(3,40)	(3,41)	(120,40,0.05)	(120,21,84,0.4)

Table A.2: Network topology parameter sets used through this work. They can be found on the notebook "network$_{p}arameters_{1}$20".

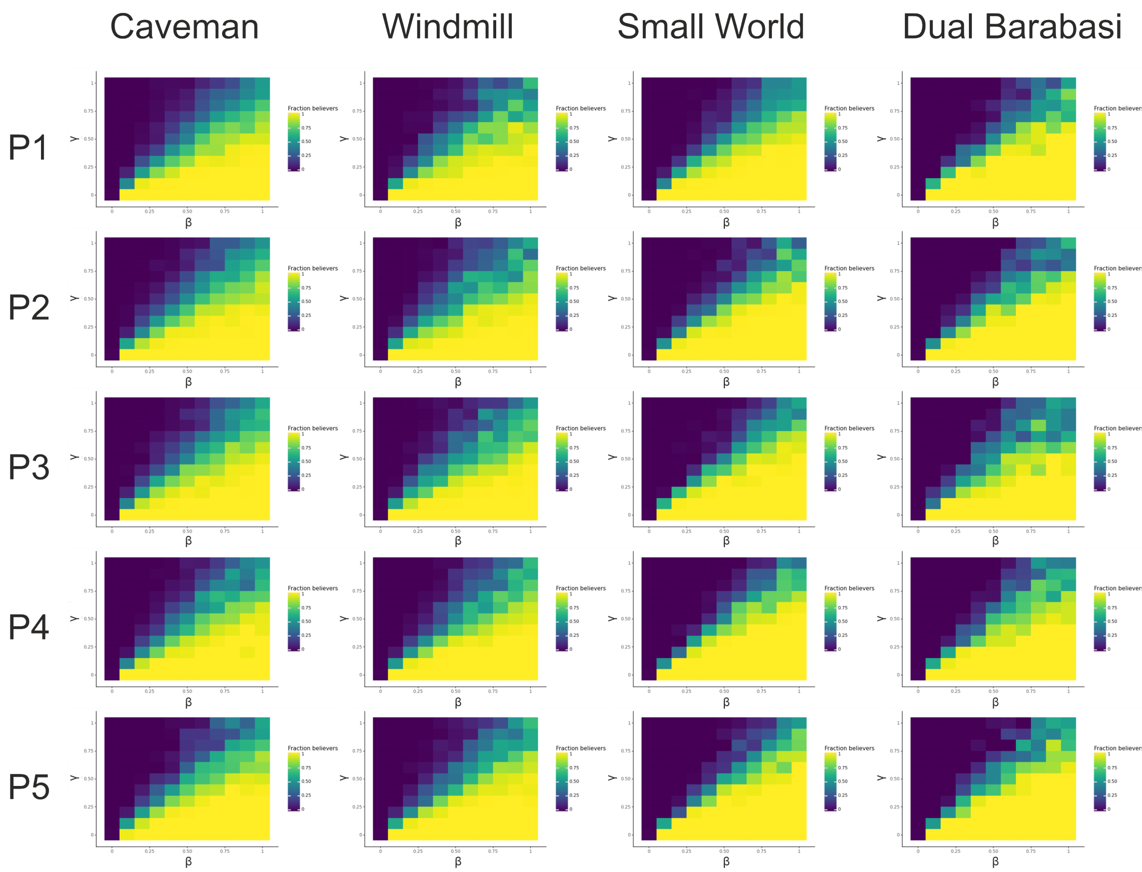

Figure A.3: **Topo 2 for 5 param.**

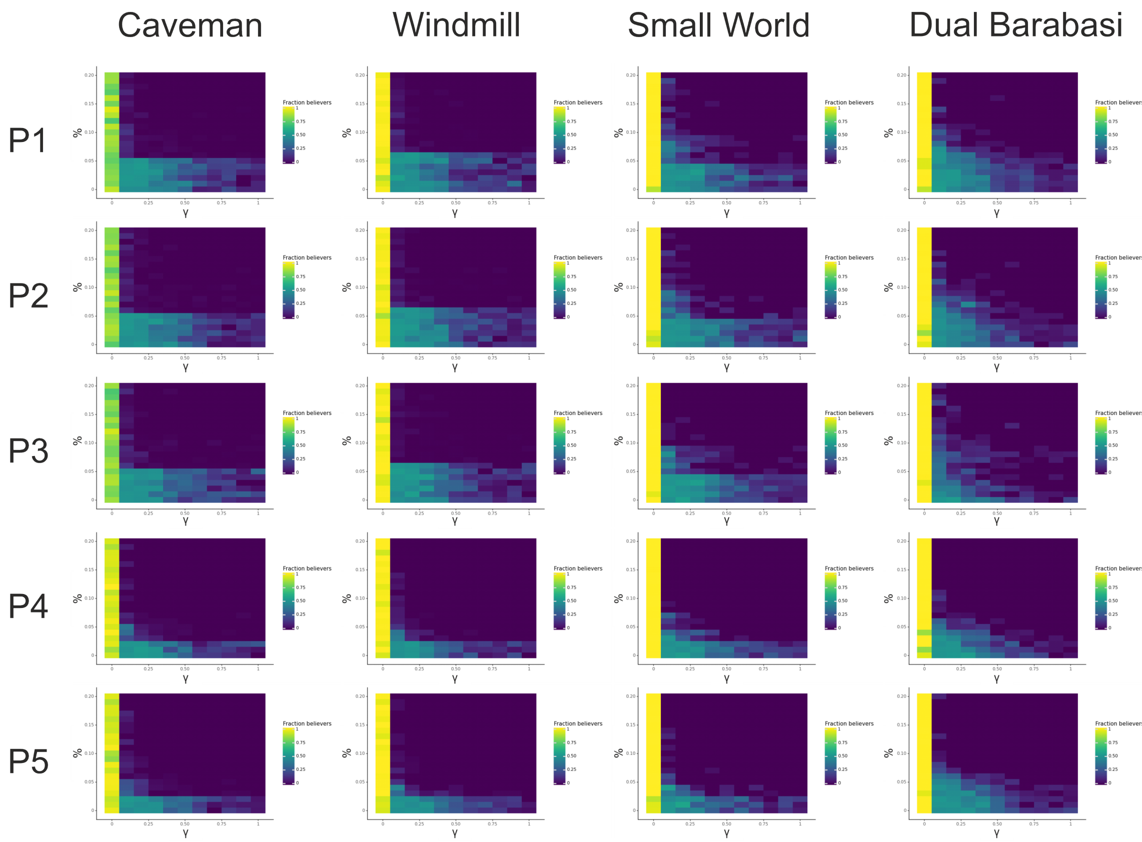

Figure A.4: **Topo 3 for 5 param**

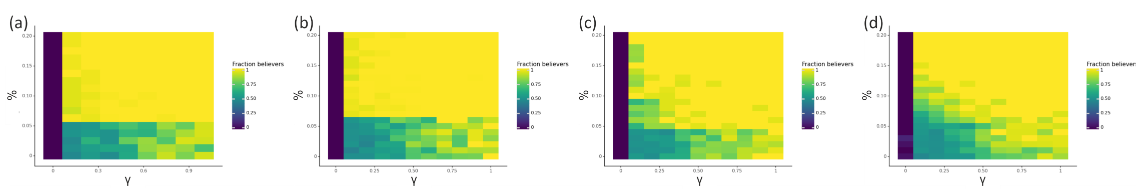

Figure A.5: **P(SI) vs neighbor threshold, param 1**