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A. P. Petrov, A. S. Akhremenko, S. A. Zheglov, E. V. Kruchinskaia

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IS NETWORK STRUCTURE IMPORTANT FOR PROTEST MOBILIZATION? FINDINGS FROM AGENT-BASED MODELING

ВАЖНА ЛИ СЕТЕВАЯ СТРУКТУРА ДЛЯ ПРОТЕСТНОЙ МОБИЛИЗАЦИИ? РЕЗУЛЬТАТЫ АГЕНТНО-ОРИЕНТИРОВАННОГО МОДЕЛИРОВАНИЯ

Alexander P. Ch. PETROV[1] *— D. Sci. (Applied Mathematics), Senior Researcher*
E-MAIL: petrov.alexander.p@yandex.ru
https://orcid.org/0000-0001-5244-8286

Andrei S. AKHREMENKO[2] *— Dr. Sci. (Political Science), Professor, School of Politics and Government, Faculty of Social Sciences*
E-MAIL: aakhremenko@hse.ru
https://orcid.org/0000-0001-8002-7307

Sergey A. ZHEGLOV[2] *— PhD Student, Doctoral School of Political Science*
E-MAIL: s_zheglov@mail.ru
https://orcid.org/0000-0002-5919-2321

Ekaterina V. KRUCHINSKAIA[2] *— PhD Student, Doctoral School of Political Science*
E-MAIL: evkruchinskaya@gmail.com
https://orcid.org/0000-0003-4778-3287

[1] Keldysh Institute of Applied Mathematics, Moscow, Russia
[2] HSE University, Moscow, Russia

ПЕТРОВ Александр Пхоун — доктор физико-математических наук, ведущий научный сотрудник, Институт прикладной математики имени М. В. Келдыша РАН, Москва, Россия
E-MAIL: petrov.alexander.p@yandex.ru
https://orcid.org/0000-0001-5244-8286

АХРЕМЕНКО Андрей Сергеевич — доктор политических наук, профессор, Департамент политики и управления факультета социальных наук, Национальный исследовательский университет «Высшая школа экономики», Москва, Россия
E-MAIL: aakhremenko@hse.ru
https://orcid.org/0000-0001-8002-7307

ЖЕГЛОВ Сергей Александрович — аспирант, Аспирантская школа по политическим наукам, Национальный исследовательский университет «Высшая школа экономики», Москва, Россия
E-MAIL: s_zheglov@mail.ru
https://orcid.org/0000-0002-5919-2321

КРУЧИНСКАЯ Екатерина Владиславовна — аспирантка, Аспирантская школа по политическим наукам, Национальный исследовательский университет «Высшая школа экономики», Москва, Россия
E-MAIL: evkruchinskaya@gmail.com
https://orcid.org/0000-0003-4778-3287

Abstract. In recent decades, the focus of civic engagement research has shifted towards studying social environments' effects on individuals' decisions on whether to participate in a given ac-

Аннотация. В последние десятилетия фокус исследований гражданской активности смещается в сторону изучения того, насколько влиятельно социальное окружение индивида в процессе приняtivity or not. Online communication has been increasingly influencing the scale of social environments as well as the features of both online and offline interpersonal communications. Surely, then, individuals' decisions concerning protest mobilization are bound to be affected by network properties. Using a series of ABM models with different network structures, we try to identify the structural factors of networks that can influence individuals who are deciding whether to join a protest. The established research in this field traditionally points to two structural factors: network topology and homophily. To our knowledge, however, the literature has not considered two above-mentioned structural factors in combination. In other words, their joint influence on protest mobilization has not been tested. To fill this research gap, we combine several network topologies with enabled/disabled homophily and examine how the combination influences protest turnout and survival. Numerical experiments show that homophily is positively associated with the survival of the protest, but negatively with its size for any network topology. Since we infer this conclusion from a theory-based computational model, we also propose how empirical testing can be conducted.

Keywords: political mobilization, political protest, agent-oriented model, network topology, homophily, social media

тия им решений. Нет сомнений в том, что современные онлайн-коммуникации воздействуют как на размеры социального окружения, так и на качество связей между индивидами даже в офлайн-среде. Что это может значить для протестной мобилизации как одного из видов гражданской активности?

С помощью агентно-ориентированной модели со включенными сетями, отражающими связи между индивидами — потенциальными участниками протеста, мы пытаемся ответить на вопрос о том, какие структурные факторы сетевой организации индивидов, принимающих решения об участии в протесте, имеют значение. Согласно сложившейся исследовательской традиции, таких структурных факторов можно выделить два: топологию сети и гомофилию. Тем не менее в уже имеющейся литературе они никогда не были соотнесены между собой, а именно, не было проверено их совместное влияние на протестную мобилизацию. Заполняя данную исследовательскую лакуну, в настоящей статье мы изучаем, как при разных топологиях сети и включенной гомофилии изменяется численность протеста и выживаемость последнего. Мы приходим к выводу, что при любых сетевых топологиях гомофилия положительно связана с выживаемостью протеста, но отрицательно — с его численностью. Данный вывод получен на основании теоретической модели, и его вклад, проверенный эмпирическим путем, нам еще предстоит оценить.

Ключевые слова: политическая мобилизация, политический протест, агентно-ориентированная модель, топология сети, гомофилия, социальные сети, социальные медиа

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Introduction

The impact of repression on street protests is controversial and commonly referred to as the puzzle of protest-repression nexus or the puzzle of punishment. One common thought is: the stronger the repression, the weaker the protest [Lichbach, 1987]. However, this is not always the case [Opp, Roehl, 1990]; sometimes the opposite obtains [Ritter, Conrad, 2016]. This paper seeks to contribute to clarifying the protest-repression nexus puzzle. Using an agent-based model with an included network structure, stimulating a network of individuals deciding whether to engage in a protest activity, we study how various group effects between individuals and network structures can influence the outcome of repression. So far, no research has raised the question of how individuals' ability to communicate in groups and the structure of social relations jointly affect the behavior of groups of protesters after repression. This paper aims to begin filling this research gap. To that end, we pay attention to both network topologies and homophily. Then, using a computational experiment, we test their combined effect on protest dynamics depending on the severity of the repression.

Thus, in this paper, we are trying to assess the ways in which a network's structure influences protest mobilization. At the same time, we appraise the combined effect of a network structure's components on protest survival. By simulating several network topologies and differing levels of homophily in a series of experiments, we also investigate whether there are any effects at all and whether there are differences in the strength of influence between homophily and topologies.

Our literature review reveals some divergence among researchers' conclusions regarding networks' topologies. The findings regarding homophily diverge even more widely. What is more, as we said, the joint effects of homophily and network topologies have not yet been studied. These circumstances open up a horizon for us to make exploring the combined effects of network topology and homophily a novel research area.

Based on the results of our simulations, we submit that for all the topologies studied in this paper, homophily is positively associated with the level of protestors' resistance to repression, but negatively associated with the number of protesters.

Literature review

The Internet as a phenomenon that allows people to quickly and easily acquire a network of acquaintances, affects not only online connections but also the communication of people in society as a whole [Bisbee, Larson, 2017]. Nowadays, people's joint actions which require coordination, cooperation, and leadership cannot be understood without first understanding individuals' networks that are facilitated by the Internet. Civic activism, including political protest, is undoubtedly such a social fact. Thus, when studying the phenomenon of political protest, it is crucial to understand

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how the Internet affects the building of network structures, i. e., how it facilitates the process of making connections [Diani, McAdam, 2009]. The structure of the network is important when examining the spread of political protest, both in terms of the dynamics of recruitment and the diffusion of information [Gonzaĺez-Bailoń, Borge-Holthoefer, Rivero, Moreno, 2011].

An interesting feature of the study of networks is that multiple aspects of a network's structure must be considered in order to understand the specific protest activity. Here, we consider two growing areas of research. One is the study of network topologies (or, less formally, architectures), which reflect a network's basic qualitative properties. Another is network homophily — the way in which connections are formed within a network, depending on the similarity of its nodes. Interestingly, research along these two lines suggests that both structural aspects of networks — topology and homophily — matter. At the same time, it is surprising that these structural aspects have not been considered by researchers simultaneously within the same study. That is what makes this paper innovative, we believe. Moreover, we will demonstrate that these structural aspects matter not only individually, but jointly.

Topology can describe how elements in a network are concerned with each other. Speaking in a general social sense, a network's topology can be conceptualized as a structure of connections in society. The study of topology as a social structure already has far-reaching implications. Thus, it is true that the ramification and size of the network affect the likelihood of an individual joining a social, political movement — i. e., collective action [Lake, Huckfeldt, 1998; McClurg, 2003]. On the other hand, a network's topology may indicate whether there are leaders or hierarchical relations in the social structure of society, or whether the connections instead are completely horizontal — this indirectly indicates, for example, the level of political awareness, and hence the propensity to participate in civil movements [Huckfeldt, 2001].

There are results — far-reaching while few — that prove that a network's topology is important for coordination. It is worth mentioning the research that opened the discussion about the matter of network topologies in the social sciences [Siegel, 2009]. It sheds light on the idea that network topology can influence the level of participation of individuals in collective action. Siegel identified four types of network topologies in which the level of participation and the speed of joining collective action are different. For example, for a topology in which "everyone is equal" and each person has the same number of links while everyone can influence even the furthest neighbor, the level of participation and rate at which people join is very high. For a similar topology with more segregated groups of people, in which individuals can only influence their near neighbors, the rate of attachment is lower. For a network whose topology may indicate it has a leader, the level of participation is highly dependent on what the leader's opinion is. For a network with a hierarchical topology, the level of participation is highly dependent on the opinion of several leaders. Continuing this idea, Siegel [2011] finds a relationship between the structure of the network and the level of participation in collective action in response to repression: repression is most likely to succeed if the network structure lacks a strong leader, one with strong and extensive connections with followers.

Another study [Piedrahita, Borge-Holthoefer, Morenoa, González-Bailón, 2018] modeling network topology and conducted in the tradition of critical mass theory

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[Granovetter, 1978] with threshold models [Kuran, 1991] also shows that network topology is important, but points out that its influence can change due to various factors. Among those factors, the authors highlight possible re-inclusion into the network and the magnitude of the network's social influence. Thus, a network's topology has a mixed effect on the coordination process, if individuals can reconnect (activate) to the network. If the network is homogeneous, coordination will be achieved quickly; if it appears unequally, then coordination is inhibited. On the other hand, if most of the connections of individuals are highly susceptible to the mechanism of social influence (individuals become similar because they communicate), topology is not critical.

Aside from models, empirical evidence [Alfonzo, 2021; Karduni, Sauda, 2020; Meraz, Papacharissi, 2013] also confirms that paying attention only to the network topology and no other structural elements leads to contradictory conclusions and creates new questions but does not answer the existing ones. A simple question arises: What other structural elements of a network should be studied in order to shed light on coordination processes — including civic engagement and protests — and are there corresponding findings in previous studies?

Individuals participating in street protests are indeed tightly connected, even online — more tightly than non-protesting individuals [Larson, Nagler, Ronen, Tucker, 2019]. What can unite the protesters so strongly, and what is the concept of the structure of the network responsible for this unification? This principle of uniting individuals can be explained by the phenomenon of homophily, another important feature of network structures.

Initially, homophily was considered as an attribute of a network and its nodes [Asikainen, Iñiguez, Ureña-Carrión, Kaski, Kivelä, 2020; McPherson et al., 2001]. Indeed, from the network analysis point of view, this concept can be defined as the nodes' propensity to form edges with others based on having similar characteristics [Jackson, Lopez-Pintado, 2013], with attributes of nodes then correlating across edges. It is important to note that homophily can be considered as a property of a network [Kim, Altmann, 2017] but it may, alternatively, simply indicate the network's structure [Bramoullé, Currarini, Jackson, Pin, Rogers, 2012]. In this paper, we are leaning towards the second way of conceptualizing homophily.

In the most general understanding of social science, homophily is the propensity of individuals to create connections with their kind [Ho, Bui, Bui, 2018] according to various social and demographic [Lazarsfeld, Merton, 1954], axiological [McPherson, Smith-Lovin, Cook, 2001], or cognitive [Song, Boomgaarden, 2017] characteristics. Thus, the more developed homophily is, the more often it is that matching individuals contact each other [Di Stefano et al., 2015]. It is also worth noting that political homophily is conceptualized in various ways. One view characterizes homophily as a state in which individuals link on a principle of discussing only "comforting" political information, which partially isolates them from political topics that might trigger cognitive dissonance [Song, Boomgaarden, 2017; Stroud, 2010]. A more conventional view has it that individuals form homophilous bonds based on common political views and ideologies [Boutyline, Willer, 2017].

It can be argued that there are quite a few types of homophily (and different definitions within these types), depending on which scientific field is being studied. However,

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it is important to draw a clear line between homophily and other, sometimes-confusing concepts. The first of these is the echo chamber. Indeed, homophily takes place when discussing the echo chamber, but the latter is a certain consequence of homophily; an echo chamber represents a common place (more frequently found in the network space) for the close companionship of individuals who are attracted by common interests or agenda [Jamieson, Capella, 2010]. Another concept, in some way derived from the echo chamber, is called the filter bubbles and constitutes a biased, personalized network search result, whereby the user is presented only with information that is in some way associated with their history of requests in the browser. Thus, the bias in the information received allows the user to see not the actual desired content but the potential desired content [Resnick, Garrett, Kriplean, Munson, Stroud, 2013]. Filter bubbles can also be explained by the proposal that "like attracts like," with the result that the individual is forced to stay in a "single" echo chamber. Finally, it is worth mentioning the concept of selective exposure. Selective exposure can be described as "manual" filter bubbles that an individual chooses voluntarily and consciously — depending on what content it is desirable to view [Frey, 1986].

Now that the concept of homophily is elucidated for this work, the next step is to clarify how homophily is accentuated with different features (e. g., features of some systems). Historically, homophily has been understood in terms of both status and value attributes [Lazarsfeld, Merton, 1954]. Homophily in status indicates that individuals with similar socioeconomic traits are more likely to converge when compared with the odds of random associations. The value attribute states that despite class similarities or differences, individuals form groups according to the principle of similarity in value attitudes. Sometimes these two attributes can work together — this has been called mixed homophily [Li, Hu, Yang, 2020]. Also, homophily is configured to develop some features of social systems, e. g., generate the spread and content of behavioral norms [Christakis, Fowler, 2007], form groups of opinion leaders and their followers [Centola, Willer, Macy, 2005], and even establish or remove barriers to information [1].

The above concepts can be useful in many ways when talking about the decision to join a protest. Individuals can follow the trend of shared values by deciding whether to participate in a protest; they can also rely on the prevailing behavioral norms in society to decide. Because we explore protest dynamics in this study, we adhere to the idea that homophily is expressed through value attitudes.

All of this being said, the effects of homophily on a broad class of social phenomena, including protest diffusion, remain unclear. A widespread point of view is that homophily has some negative social consequences: polarization and fragmentation [Levendusky, 2013] of opinions, which subsequently tend to increase the appearance and proliferation of echo chambers [Dandekar, Goel, Lee, 2013] and selective exposure [Stroud, 2010]. This view originates from Schelling's [1971] model, which shows that the presence of homophily leads to levels of segregation that greatly exceed individual needs for similarity.

Another stream in the literature argues that homophily can be worthwhile in societies where there is a lack of collective solidarity and identity [Collins, 1993]; associa-

[1] Choudhury M., Sundaram H., John A., Seligmann D., Kelliher A. (2010) "Birds of a Feather": Does User Homophily Impact Information Diffusion in Social Media? (Research Paper). URL: https://arxiv.org/abs/1006.1702 (accessed: 28.11.2021).

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tions of people with common interests can resolve this problem. Likely, this can lead certain parts of society (connected by homophilous ties) to mobilize in terms of open expression of citizenship, participation in protests [Polletta, 1998], and mobilization of other collective actions [Centola, 2011]. This can be considered a positive corollary since in some way it is the solution to the problem of coordinating societies of like-minded people to achieve the common good [Macy, 1990].

Some studies point out the mixed and non-linear effects of homophily. For example, it is important to note the results of game-theoretic modeling of the emergence of revolutions and uprisings [Barberà, Jackson, 2020]. The success of these events is tested at the different levels of homophily inherent in the participants in the movement. Thus, Barberà and Jackson [2020] conclude that high levels of homophily leading to a more homogeneous society, the absence of widespread social segregation, is positively associated with the possibility of insurrection, while the opposite situation — low homophily and high segregation — are negatively associated with the possibility of insurrection. No less interesting are the results of the model of the spread of collective action [Korkmaz, Kuhlman, Goldstein, Vega-Redondo, 2020]. In this case, it was found that a high level of homophily, on the one hand, is positively associated with joining collective action; on the other hand, with high levels of homophily joining participants to collective action related to a high degree of non-linear and non-monotonic trends. In other words, homophilous connections help in the search for new members of collective movements, but the process of this connection can be described as rather chaotic.

There is also a diametrically opposite result obtained by modeling. For example, according to the model of the formation of social opinions [Degroot, 1974], homophilous structures of ties can constitute a potential threat for communities to polarize. This idea was extensively developed by Bindel, Kleinberg, Oren, [2011] and Krause [2000]. These results were supplemented with the idea that for homophily to work for polarization, an additional but key determinant is needed: biased assimilation (or confirmation bias, i. e., a tendency to justify one's point of view).

Importantly, there are even more contradictory results. For example, from the perspective of an agent-based model designed to study the relationship of homophily and behavior diffusion, Li, Hu and Yang [2020] concluded that homophily positively influenced behavior diffusion only when individuals were inclined to adapt their opinions; otherwise, homophily had the opposite effect and reduced behavior diffusion. In addition, Li et al. argue that the influence of homophily has a similar sign but differs in value impact on behavior diffusion, depending on its nature (status or value).

The empirical evidence for results is not as extensively studied but can also be called divergent. For example, there is evidence that homophilous ties can contribute to the emergence of close communities with a clearly expressed political position; then being in these communities makes it difficult to perceive an opposing political position [Boutyline, Willer, 2017]. This means that homophily can mobilize ideological guidelines. The ideological wing which has the most individuals and communities with homophilous connections will be the most radical, and its community will be more closed to external influence. On the flip side, some results indicate that homophilous connections in social media create a stable pool of communities for the exchange of political information (for example, Hong Kong movements) that support each other by exchanging and sending content, but do not create additional conditions for isolation from separate communities [Zhang, Lee, 2018].

It would be an oversight to ignore the rich potential of research results, both for network topology and homophily. By highlighting the controversy of the previous research results about topology and homophily impact on protest mobilization, we hope to have illuminated the point of studying both structural factors concurrently. In the next section, we discuss the specifics of the methodology used in this paper, to explain how agent-based modeling principles were implemented in prior research and to explain how we implement them to explore the network and its structure.

Networks and Homophily in an Agent-Based Framework

Our methodology for tackling the above research problem is agent-based modeling (ABM). Agents are a system of autonomous elements capable of being in a finite number of states at discrete periods of time. In the broadest class of modeling problems associated with human behavior, agents represent individuals making decisions; switching from one state to another is analogous to making a choice between alternatives. The state of an agent depends both on individual properties and on the states of other agents associated with her (for detailed overviews of ABM methodology, see [Akhremenko, Petrov, Zheglov, 2021; Laver, 2020; Bonabeau, 2002; Wilensky, Rand, 2015]).

This general framework fits our research question optimally, for several reasons. First and foremost, it allows agents to be explicitly integrated into network structures. In recent years, this very opportunity has largely determined the growing popularity of ABM among social scientists [Amblard, Bouadjio-Boulic, Sureda Gutiérrez, Gaudo, 2015; Cercel, Trausan-Matu, 2014; Will, Groeneveld, Frank, Müller, 2020]. Researchers of contentious politics have recently used this approach to study the mechanisms of actors' coordination [Piedrahita et al., 2018], the impact of authority centralization and social network technology on large-scale institutional change [Makowsky, Rubin, 2013], coevolution of topics of concern as a condition for the emergence of large social protests [Asgharpourmasouleh, Fattahzadeh, Mayerhoffer, Lorenz, 2020], the influence of non-local connections on civil violence dynamics [Fonoberova, Mezić, Mezić, Hogg, Gravel, 2019], the effect of social tolerance and interconnectivity upon the radicalization of politics [Dacrema, Benati, 2020], the role of armed organizations in political revolutions [Moro, 2016], and many other issues.

As a rule, researchers tend to work with some definite network topology, varying its settings. The most widely used network architectures are "Small World" [Watts, Strogatz, 1998], which aims to represent traditional communication networks, and "preferential attachment" [Barabási, Albert, 1999; Barabási, Albert, Jeong, 2000], which is more consistent with the structures of communication in social media. Small World architecture is a combination of a regular graph, where each node has a fixed and equal number of neighbors, and a random network [Erdös, Rényi, 1959; Stocker, Green, Newth, 2001]. The regular component represents an individual's everyday social environment — so-called "strong ties"; the random network, in contrast, is associated with weak ties with people who do not belong to the inner circle of the individual's communication. The preferential attachment network is based on the "the rich get richer" principle: the probability of a new link joining a given node depends on

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how many edges are already attached to it. This algorithm results in a typically large social media unevenness in the number of network connections (subscriptions, friends, followers, etc., see [Amblard et al., 2015]).

In some cases, an individual's network environment is implemented in the model simultaneously with their spatial neighborhood. The original, and still widely used way of simulating the interaction between agents is the cellular lattice, in which the neighborhood is determined by the geometric proximity of agents to each other. Some researchers modify this classical approach by integrating a certain network type (see e. g., [Fonoberova et al., 2019; Makowsky, Rubin 2013]). As in the previous case, variation of the network parameters (rewiring probability, network size, average degree, etc.) is usually a part of the experiment.

However, from our perspective the most promising approach — still not very common in the literature — is to test the effects of different topologies within the framework of one model. Following Piedrahita et al. [2018] and Siegel [2009; 2011], which are good examples of this design in research on contentious politics, we use five alternative network architectures: the already named Small World and preferential attachment as the baseline architectures, and the regular, complete, and random graphs as the controls.

Along with the wide applicability of network options, an important advantage of ABM is its capacity to simulate complex dynamic processes. This is due in particular to the fact that the model simulation's duration in ABM is practically not limited by anything other than computing power. The focus of this research is not just individual protest actions, but protest campaigns — interconnected sequences of protest events evolving over time. Network effects do not manifest themselves instantly; the interplay of information and influence in the network takes time. Both in real life and in our model, the successful course of a protest campaign occurs through a step-by-step increase in the number of protesters. One of its key mechanisms is protest cascades, where those who have already taken to the streets motivate hesitant agents to join [Kuran, 1989; Granovetter, 1978]. Protest cascades are fundamentally dynamic phenomena whose study requires a nuanced picture of processes development over time. Such a picture cannot be obtained within the framework of the main competing modeling methodology in the social sciences: game theory. Although there certainly exist noteworthy and clever game-theoretic models of protests (see e. g., [Little, 2016]), including those that incorporate homophily [Barberà, Jackson 2020], they are invariably limited to the analysis of final equilibria, without considering the patterns of protest dynamics.

The implementation of homophily in computational and mathematical models is a separate important task with its own special difficulties. The standard approach, originating from Schelling's [1971] seminal segregation model, which we have already discussed above, is to define several (usually two or three) qualitative types and to assign each agent to one of them. For example, Holzhauer, Krebs, and Ernst [2013] specify three types of agents: "right" extremists, moderate, and "left" extremists. Next, a square matrix is compiled, with the number of rows and columns equal to the number of types in question, which determines the probabilities of the link formation between them [Dandekar et al., 2013; Korkmaz et al., 2020; Holzhauer et al., 2013], e. g., how

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likely it is that a right-wing extremist will be linked with a moderate agent. It is natural to assume that, in the presence of homophily, the probability of making a connection is higher if both agents are of the same type. But how much higher? And how should the probabilities of connection with “alien” types be determined if there are more than two types in the model?

In our model, the attribute-generating homophily is of a quantitative property (measured at the interval level), not a qualitative property. An individual’s decision to participate in a protest is based upon a mechanism that includes two components. The first, dynamic component is a “net force” of short-term campaign factors: the situational influence of the social environment, an assessment of the chances of suffering from repression, and group efficacy belief. The second component, which we call an attitude, is a long-term predisposition towards participation in a protest, determined by a large set of heterogeneous determinants, from social status and demographic characteristics to value orientations. It is the second component that creates homophilous relationships in the model. Being a continuous value, the attitude provides pairwise distances between agents. The letter, being a natural measure of proximity, becomes the basis for calculating the probability of connections between nodes. (Ho et al. [2018] take a similar approach).

We implement homophily in the procedure of initialization of three of five topologies: Barabási — Albert (preferential attachment), Watts — Strogatz (Small World), and Erdös — Rényi (random) graph (the remaining two topologies exclude the possibility of implementing homophily in their initialization process). In all versions of topologies, the probability of a connection between network agents depends on the Euclidean distance between them. The role of homophily in the creation of the network is regulated manually and is set as a separate parameter. The key characteristic that defines the similarity between agents is the attitude, which is unique for each agent. More details about implementation homophily in the procedure of initialization of three topologies can be found in Appendix A.

The Model

We consider the preferential attachment network to be an analogue of communication on the Internet. The Small World network represents more traditional ties, while the random graph serves as a control. Thus, at the heart of this model lies the principle of testing alternative network topologies, each of which is integrated with a homophilous mechanism. This will allow us, we hope, to better address the key question of this work: What is the joined effect of network topology and homophily on protest participation?

The model focuses on the dynamics of turnout on subsequent instances of a protest campaign. The driving force behind this dynamic is: the greater “yesterday’s” turnout, the greater the motivation for participation in today’s protest event. Accordingly, the model centers on the decision-making of potential protesters on whether to attend “today’s” event. It is convenient to imagine an individual having her breakfast and weighing motives for participation against motives for non-participation, while also taking into account individual-specific long-term predisposition. Thus, our approach distinguishes between short-term and long-term factors of protest activity. Short-term

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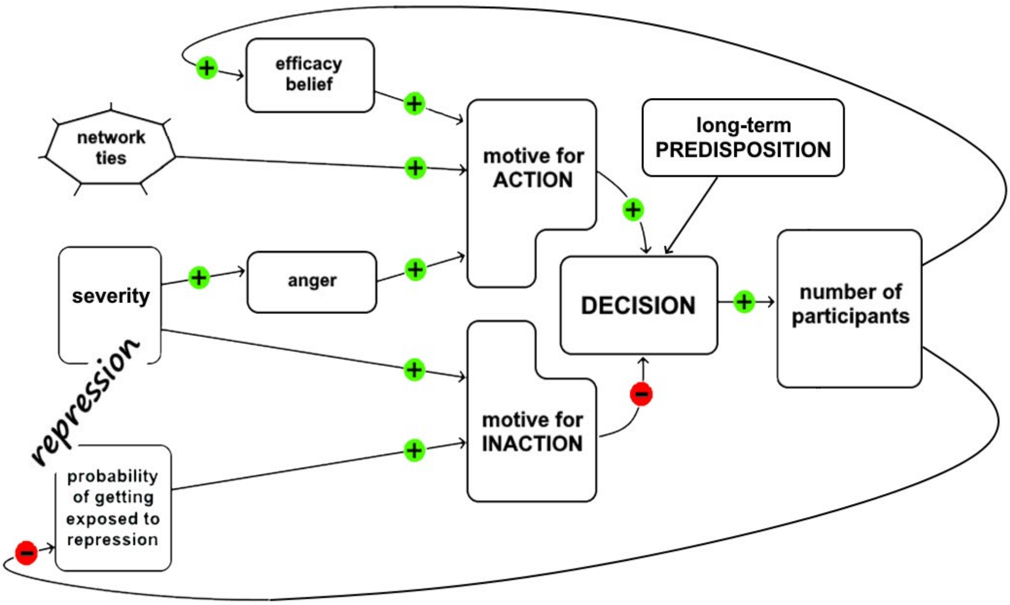
factors are those which change over time during the protest campaign, namely, turnout and severity of repression. Long-term factors, such as disposable income or religious attachment, are constant during the campaign. They do not explicitly present in the model but are assumed to be aggregated in the individual-specific attitude.

The logic of the model is shown in figure 1. The core box is Decision. It is influenced by the motive for action $M_{action}(t)$, the motive for inaction $M_{inaction}(t)$, and attitude φ, which is a constant over time being the measure of long-term predisposition. The individual attends the protest action on day t if and only if

$$\varphi + M_{action}(t) - M_{inaction}(t) > 0.$$

It follows from this that participants on day t are those individuals whose attitudes φ are large enough: $\varphi > -\psi$ where ψ is the full motive: $\psi = M_{action}(t) - M_{inaction}(t)$. Both motive for action and motive for inaction depend on the expectations of attendance and severity of repression.

Fig. 1. The scheme of the mathematical model



By assumption, the aforementioned “breakfasting” individual makes her projections based on the previous day’s attendance $P(t-1)$ and the greatest severity of repression from the previous days, which we denote as $s(t-1)$ (alternatives would be to take the last-day severity or the greatest severity from the period after the latest concession by the government). The formulae are given in Appendix B; here, we present graphs and considerations.

The motive for inaction is an increasing function of severity because it deters individuals from participation through fear (fig. 2).

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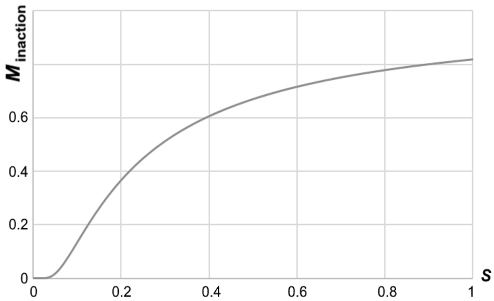
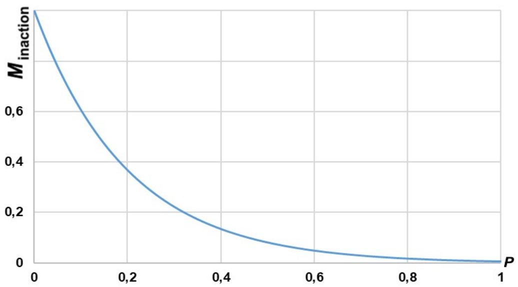
Fig. 2. The motive for inaction as a function of severity



At the same time, it is a decreasing function of turnout (fig. 3), because greater numbers of participants reduce any particular person's likelihood of being exposed to repression (the so-called safety-in-numbers proposition; see [Kuran, 1991; Lohmann, 2019]).

Fig. 3. The motive for inaction as a function of turnout



The graphs in figure 2 and figure 3 correspond to the specification given in Appendix B.

The motive for action is influenced by a range of factors through the mediation of three psychological antecedents, which are anger, efficacy belief and protest identification of the individual [Ayanian, Tausch, 2016; Van Zomeren, Postmes, Spears, 2008]. Specifically, repression fuels participation by mediation of anger, and the number of protesters affects the motive for participation through efficacy belief (fig. 1). It is worth noting that repression adds to both motive for action and motive for inaction.

Local environments can become involved through reasoning such as, "It not only matters how many people are protesting, but also how many of my friends are". To take the local environment into account, the model treats individuals as nodes of a network, with edges corresponding to the ties between them. Thus, when deciding whether to attend, the "breakfasting" individual looks both at macro variables (the total number of protesters) and at local variables (the number of protesters with whom she has ties).

Network affects the motivation. It realizes the concept of a normative motive introduced by Klandermans [1984] (see also [Stürmer, Simon, 2004]). In this paper, the classification of motives for participation is presented, where a normative motive is described along with a collective motive (associated with the strict goal of the action,

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for example, to topple the government) and a reward motive (associated with reward for participation as the process, including the pleasure of spending good time at a rally or payments from the sponsors of the protest). The normative motive suggests that the social environment of an individual forms a local norm for behavior. Put simply, in some circles taking part in protests may simply be expected. Defying this norm may entail disappointing friends and losing their respect. Accordingly, the model assumes that the strength of an individual's normative motive for participation increases with the number of her friends who are already involved.

Homophily Effects: The Computational Experiment and its Result

The main goal of the computational experiment is not to see how network structure alters the efficacy of repression [Siegel, 2011: 1000] but rather to see how the manner of initializing the network structure alters the efficacy of repression. Thus, we omit discussion of prior results concerning our first acquaintance with the model (but see the main findings of [Akhremenko, Petrov, 2020]).

The computational experiment consists of conducting a set of simulations according to a given system of equations and rules, i. e., the computational model computes the game-theoretic equilibrium numerically [Siegel, 2018: 750]. Within our model each simulation run starts with the initialization of the network and the assignment of personal attitudes to agents (i. e., to nodes of the network). Thus, the model has two stochastic components. After the creation of a network, the process of contest begins with agents deciding whether to protest or not, depending on the sum of motives and long-term personal attitudes toward protest. In this first stage, initial anger plays the most important role, since there are no protesters yet, nor is there any repression; a trigger is required. Then, in the second stage, authorities reveal the severity of repression they use and apply it. In the third stage, the agents update their decision according to the previous decisions of their friends and the changes in the share of protesters, and the severity of repression. The third stage is repeated until the simulation comes to an equilibrium (but no more than 100 times). An equilibrium state is reached if no agent changes her dissent status within 20 consecutive periods.

We use the technique of grid search to extract descriptive statistics for assessing network effects on the efficacy of repression. The grid search is the method of parameter sweeping for sequential enumeration of exogenous parameters, on the basis of which the simulation is run. We went through the parameters of severity (from 0 to 1 with step 0.1), network topology (five types: Watts — Strogatz, Barabási — Albert, Erdös-Rényi, regular graph, and complete graph), and homophily (0, 1, 10, 100). We should note that the zero value of a parameter of homophily means that it is a clear type of network topology. Since we sweep only three exogenous parameters, all interactions were detectable by the human eye; thus, descriptive statistics is sufficient for analyzing the results.

For each of 220 (11*5*5) unique sets of parameters, we calculated two summary characteristics based on 100 simulations. Firstly, the *survival probability of protest* is calculated as the number of simulations in which protest still exists in equilibrium divided by 100 (the number of simulations). Secondly, the *participation rate of survived protest* is calculated as the mean equilibrium share of protesters in simulations in which protest still exists in equilibrium.

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Fig. 4 presents the severity repression effects on the survival probability of protest depending on the network topology and homophily parameter. First of all, we see that the survival probability decreases with increases in the severity of repression in all cases. Moreover, the figure indicates that when the severity of repression is less than 0.5, the survival probability of protest is equal to one regardless of the type of network topology and the value of the homophily parameter. Only with the severity of repression growth from 0.5 does the probability of protest survival start to decrease.

Fig. 4. Dependence of the survival probability of protest on the repression severity

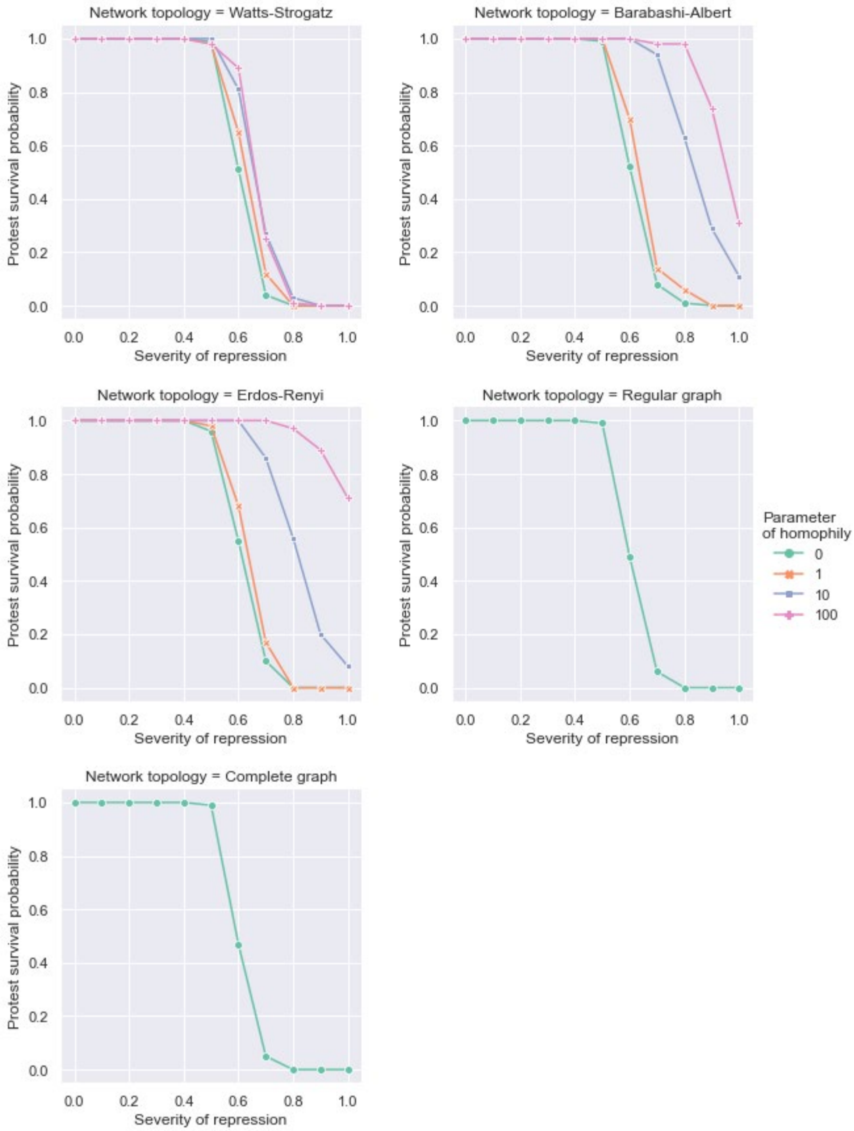

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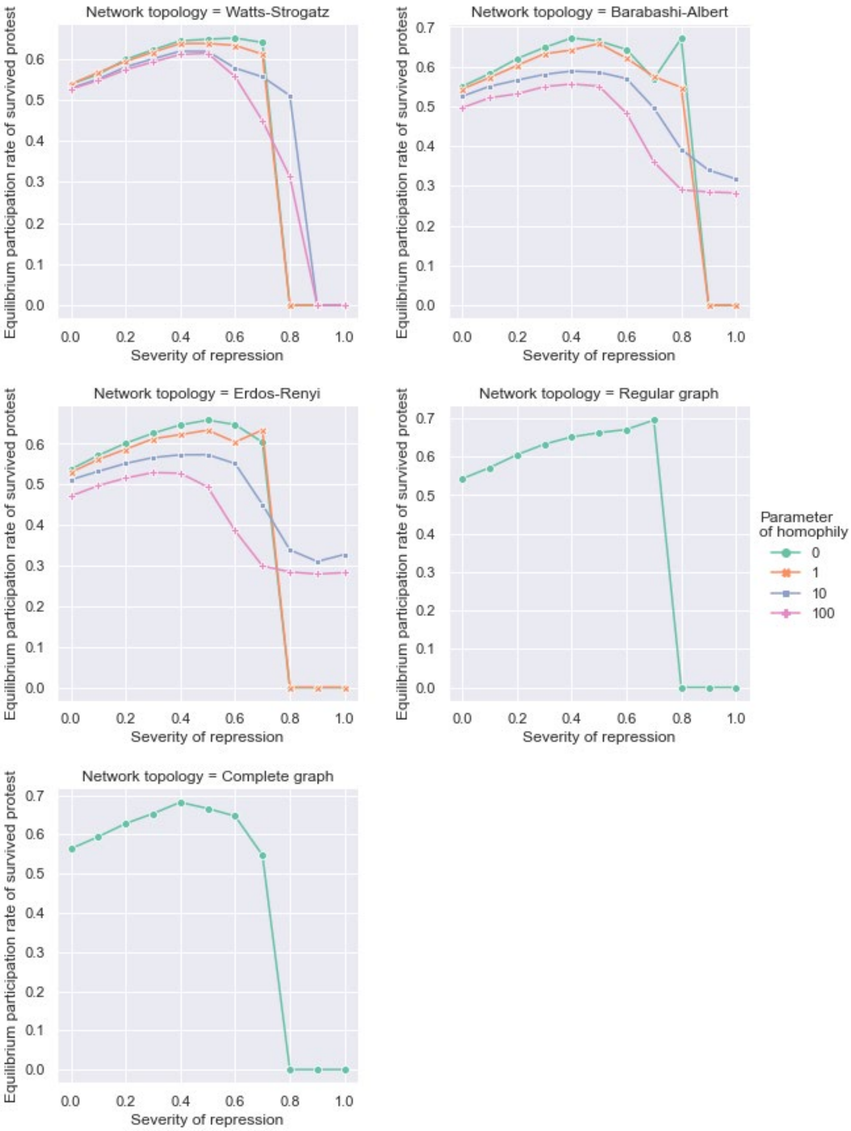
Fig. 5. Dependence of the participation rate of survived protest on the repression severity



Comparison between plots with different topology types reveals the common pattern that the higher the value of the homophily parameter, the more likely it is that the protest will survive in equilibrium when the severity of repression is more than 0.5. This is the evidence that the formation of a cohesive group of like-minded agents helps their protest movement to survive due to mutual motivation of each other in favor of participation. As we see from the first to the third plot (complete and regular graphs are represented for robustness), the higher the value of the homophily parameter

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(i. e., the more cohesive the alliance of dissents and the less connections it has with a backward society), the more resistant the protest is to repression. The increases in probability to survive with higher values of homophily parameters are much more substantial for models with Barabási — Albert and Erdös — Rényi topologies compared to those with the Watts — Strogatz topology. The reason is that the value of the homophily parameter affects only 30 % of all connections within a Watts — Strogatz topology since the default rewiring probability is equal to 0.3. In contrast, 100 % of the connections are based on the homophily parameter within Barabási — Albert and Erdös-Rényi topologies, since the process of initialization of these networks does not include any rewiring.

The five plots in figure 5 demonstrate the repression effects on the participation rate of survived protest depending on the network topology and homophily parameter. We see a reverse U-shape relationship: firstly, the participation rate of survived protest grows with increases in severity of repression but then starts decreasing (except for the regular graph) until the protest could survive; otherwise, it reaches zero. Comparison between plots with different values of the homophily parameter demonstrates that increases in that value result in lower participation rates.

In other words, *homophily improves the level of resistance of protesters to repression* (as follows from fig. 4) *but negatively affects the number of protesters* (as in turn follows from fig. 5). This is the key result of the computational experiment.

Conclusion & Discussion

In this paper, we posit the general idea that the structure of the network for protest mobilization matters. We present the ABM model applied to a network of individuals, each of whom decides whether to attend a protest, taking into account the previous day's decisions of network neighbors. By simultaneously examining the effects of topology and homophily, we demonstrate that what really matters is their combination, whereas neither is especially powerful in its own right. For each topology with homophily enabled, the survival rate of the protest increases with homophily, although the number of protesters decreases.

It is also important to highlight some of this model's limitations. One of them is typical for this kind of model, and it deserves special attention since it indicates a promising direction for further research in the entire field. To test the effects of various topologies, we, like most other researchers in this field, use several alternative structures: Small World, preferential attachment, random graphs, etc. However, none of these structures simultaneously reproduces all the essential properties of human social networks, such as local clustering, short average path lengths, and highly skewed degree distribution [Steinert-Threlkeld, Steinert-Threlkeld, 2021]. Thus, scholars of communication and social networks face the fundamental challenge of developing models that will more accurately match real-world network structures.

Our second limitation is related to the distribution of attitudes (long-term predispositions) towards participation in a protest. In this study, we only test the uniform distribution, and not just for the sake of simplicity. There is at least one piece of empirical evidence that this variable is indeed uniformly distributed [González-Bailoń et al., 2011]. However, since that is the only paper (to the best of our knowledge) that

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attempts to measure this property, and it only deals with the online protest in Spain, further efforts are needed to clarify this issue.

Regarding the upcoming empirical testing of the model's predictions, Larson et al. [2019] suggest a promising approach. They examine the network ties of those who participated (in comparison to those who did not) in the 2015 Charlie Hebdo protest in Paris. The sample was formed from individuals who published messages in support of the protest event on social media (Twitter, in this case). Using geolocation, the sample was split into two subsets. The first included those participating offline, i. e., whose messages were geotagged to be within the protest site. The second, which was used as a comparison set of the same size, consisted of people who were physically close to the place of the protest (and therefore had the opportunity to take part in it) but did not participate. At the next stage, full online networks were reconstructed for both the protestors and the comparison set, including all the connections of the participating and non-participating ones.

Such data allows us to operationalize the key variables of the model. Firstly, measuring network parameters such as clustering level, average path length, and vertex degree distribution will help determine the topological properties of the network. Secondly, analyzing the groups or accounts those users follow will make it possible to estimate their attitudes. Together with the network structure, this yields the overall level of homophily in the network. The latter can be obtained using such applied network analysis methods as latent space models or stochastic blockmodels (see, e. g., [Ng et al., 2020; Faust, Wasserman, 1992]). Finally, repression rate data can be obtained based on the number of arrests and victims of police violence.

A possible alternative to the rather complicated strategy described above is to use more traditional survey methods. However, their results may not be sufficiently valid in repressive environments, which are of particular interest for this study. In addition, there are of course obvious difficulties with the selection and availability of respondents.

The study of network determinants of protest activity in the presence of repression remains one of the most understudied and challenging endeavors of modern political science and political sociology. We hope that our work outlines some promising directions for further research.

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APPENDIX A

The current version of the model supports homophily-based creation of networks for three topologies: Barabási — Albert, Watts — Strogatz, and Erdös — Rényi graphs (all are undirected, with the exception of one version of the Erdös — Rényi graph, which we do not use).

(1) Barabási — Albert

A variant of the implementation of homophily in the Barabási — Albert network is borrowed from the existing work [Gargiulo, Gandica, 2017]. The Barabási — Albert network is also called a preferential attachment model, meaning that the probability of attaching a new vertex for previous ones depends on their degree. Firstly, *m* nodes are selected out of *N* and a complete graph is built on these vertices; then each of the remaining vertices is alternately added to this graph, connecting with the *m* number of vertices. Each vertex of the graph has its own probability of connecting to new vertex. That probability depends on the degree of vertex (*k*) and is calculated according to the following formula:

$$\varphi_j(i) = k,$$

$$P_{i \leftrightarrow j} = \frac{\varphi_j(i)}{\sum_{v=1}^{m+i} \varphi_v(i)}.$$

The homophily is implemented in the network initialization process via this formula: the more similar two vertices are, the greater their chances of being connected by an edge. The formula below uses distance, i. e., an inverse-similarity indicator. The power of adjustment depends on the homophily parameter. This can be represented in the following form, where β is the homophily parameter, and $|\theta_j - \theta_i|$ is the distance between the vertices:

$$\varphi_j(i) = k \times \exp(-\beta \times |\theta_j - \theta_i|).$$

(2) Watts — Strogatz

We could not completely borrow the algorithm above for implementing homophily-based initialization for other graphs in view of a different graph generation process, but we were guided by the same approach.

The process of initializing the Watts — Strogatz network involves ensuring that each vertex is connected to the *k* (always even) number of the nearest (by the looped index) vertices. Then the connection of each node is sequentially broken with probability *p* (i. e., rewiring probability; this is equal to 0.3 in our computational experiment), and the new connection appears between this node and a randomly selected one from those with which this node has not yet been connected:

$$\varphi_j(i) = \begin{cases} 0, \text{ if } i \leftrightarrow j \\ 1, \text{ otherwise} \end{cases},$$

$$P_{i \leftrightarrow j} = \frac{\varphi_j(i)}{\sum_{v=1,\, v \neq i}^{N} \varphi_v(i)}.$$

Accordingly, homophily is introduced precisely in the process of rewiring. Now each connection of a vertex with probability p is broken and its probability of connecting to new vertices is proportional to the distance between it and the other vertices, respectively:

$$\varphi_j(i) = \begin{cases} 0, \text{ if } i \leftrightarrow j \\ \exp(-\beta \times |\theta_j - \theta_i|), \text{ otherwise} \end{cases}.$$

(3) Erdös — Rényi

The logic of constructing a random Erdös — Rényi graph differs from the two above graphs in simplicity. The probability of any connection in the graph is the same. Thus, there are $N^2/2$ possible connections in an undirected graph of N vertices; each of these connections has the same probability of creation:

$$\varphi_j(i) = 1,$$

$$P_{i \leftrightarrow j} = \frac{\varphi_j(i)}{\sum_{v=1}^{N^2/2} \varphi_v(i)}.$$

Accordingly, with the introduction of homophily, the probability of creating a connection between two vertices begins to depend on the probability, adjusted for the proximity of two vertices in the network:

$$\varphi_j(i) = \exp(-\beta \times |\theta_j - \theta_i|).$$

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APPENDIX B

Individual i on day t makes a positive decision to participate in the protest if and only if her latent position $\lambda(t, i) = \varphi(i) + \psi(t, i)$ is positive. Here $\varphi(i)$ is her attitude, that is, predisposition towards participation. $\psi(t, i)$ is the arithmetic difference between the motive for action (participation) and the motive for inaction (non-participation): $\psi(t, i) = M_{\text{action}}(t, i) - M_{\text{inaction}}(t, i)$. The motive for action is calculated using the formula:

$$M_{\text{action}}(t+1, i) = 1/3\ [(a(t) + b(t) + M_{\text{norm}}(t+1, i)].$$

Here $a(t)$ is anger, $a(t) = (a_0 + s(t))\,/\,2$, where a_0 is anger caused by the trigger event and $s(t)$ is anger caused by the severity of repression. Next, $b(t)$ is efficacy belief:

$$b(t) = \exp(k_B(P(t) - P_0))\,/\,[1 + \exp(k_B(P(t) - P_0))],$$

where k_B, P_0 are constants, and $P(t)$ is the turnout on day t. The normative motive $M_{\text{norm}}(t, i)$ represents the fraction of the agent's ties who participated in the protest on the previous day in the total number of her ties. The motive for inaction has the form:

$$M_{\text{inaction}}(t+1) = \exp(-cP(t)\,/\,s(t)) \text{ if } s(t) > 0,$$

$$M_{\text{inaction}}(t+1) = 0 \text{ if } s(t) = 0.$$

where c is a positive constant. For further details, see [Akhremenko, Petrov, 2020].