Modeling the Protest-Repression Nexus

Andrei Akhremenko[a] and Alexander Petrov[a,b]

[a] National Research University Higher School of Economics, 20 Myasnitskaya Str., Moscow, 101000, Russia
[b] Keldysh Institute of Applied Mathematics RAS, 4 Miusskaya sq., Moscow, 125047, Russia

Abstract
Over the last 30 years, numerous studies have shown that repression can de-crease, increase, or have some kind of a nonlinear or mixed impact on the intensity of protest. This problem is usually referred to as the "protest-repression nexus" or the "punishment puzzle", and it is still not resolved. The mathematical and computational model that we present in this paper is intended to shed new light on the causes of puzzling contradictions in empirical results. Building upon micro-level approach to political participation, we demonstrate that the reaction of protesters to repression can be dramatically different under the virtually same conditions. We show that an increase in repression levels leads to a more pronounced division between two possible outcomes of a contentious political event: successful protest and failed protest. The model highlights the importance of the intensity of the government's repressive reaction to protests. The more disproportionate ("nervous") this reaction is, the less stable the situation becomes. The latter means that the protest will either be suppressed or become extremely massive, but it is unlikely to remain moderate. Both findings are qualitatively similar and emphasize our general finding: the suppression of protest makes its further course less predictable. Methodological contribution of the paper is that our model allows for accounting both fueling and stifling effects of repression on participation within the same model specification.

Keywords
Protest, Repression, Formal Model, Dynamical Model, Computational Model

1. Introduction

In 1987 the famous conflict researcher Mark Lichbach wrote: "Aggregate data studies of domestic political conflict have… produced contradictory findings about the repression/dissent nexus: repression by regimes may either increase or decrease dissent by opposition groups" [1]. Nowadays, more than thirty years later, another scholar recognizes that "recent reviews of research on state repression highlighted contradictory findings about this effect, yet the core question is still debated: what accounts for the variation in the effects of repression?" [2].

Indeed, despite the dramatic growth of the body of literature, that has taken place over the past decades, the "punishment puzzle" remains unresolved. Empirical studies still demonstrate that repression can decrease, increase, or have some kind of a nonlinear or mixed impact on the intensity of protest. In the latter case, various intermediate determinants enter the scene, such as the type of political regime [3], organizational infrastructure of the protest movement [4], coercive capacity of the state [5], split in the elites [6], "memory of violence" in the aftermath of civil wars [7], ICT's penetration rates [8], and many others.

The variety and number of these factors – structural in their nature – is alone more embarrassing than shedding light on the true causal mechanisms of protest backlash. Not to mention the evidence that the response to repression may vary substantially under the similar structural conditions [2]. The modelling results we present in this paper fully confirm this observation. Moreover, we show that the reaction of protesters to repression can be dramatically different under the exact same conditions.

Modeling and Analysis of Complex Systems and Processes - MACSPro'2020, October 22–24, 2020, Venice, Italy & Moscow, Russia
EMAIL: ahremenko@yandex.ru (A. 1); petrov.alexander.p@yandex.ru (A. 2)
ORCID: 0000-0001-8002-7307 (A. 1); 0000-0001-5244-8286 (A. 2);

We highlight several key reasons of the difficulties that the prevailing research tradition faces to explain the protest-repression nexus. Firstly, its de facto macro-level view ignores individual variation in the motives and incentives for protest participation. Secondly, it tends to address the problem in terms of dependent and independent variables, considering the level of protest as a function of repression, which leads to overlooking any feedback loops. The two named features explicitly manifest themselves in the dominant tool of corresponding empirical research – regression models with data aggregated, mostly, at the country-year level. Third, not enough attention is paid to the emotional component of this problem, while both common sense and the literature [9] indicate its special importance for the emergence of protest backlash.

Our goal in this study is to propose a mathematical model that fills the gaps indicated above. We build upon a micro-level approach to political participation, with the special emphasis on the socio-psychological factors of collective action [10]. In this view, repression does not only increase the costs for protesters, as in the traditional rational choice theory, but also stimulates group cohesion, increases "social rewards" for participating, and, thus, encouraging new participants to join the protest [11, 12]. The protest can also be enhanced due to increased group identification, the effect of "common fortune", together with the feeling of suffering from illegal persecution [13]. In these approaches, of great importance is the moral justification of retaliatory violence [14], and, especially, the emotional reaction to repression – anger or outrage [15].

Another cornerstone of our model is the consideration of the protest as a continuous event, a dynamic process with feedback loops. This idea, of course, is not new; at the end of the last century, Rasler [12] pointed out that "timing matters": repressions are effective in the short term, but are likely to stimulate protest over a long time horizon. It has also been observed that repression and protest "are influenced by themselves" (are auto dynamical, in other words) [16] and have "inertia" [17]. Sullivan and coauthors [18] claim that the impact of repression can vary depending on whether the dissent is on the rise or in decline.

However, in contemporary research, studies that specifically address repression and protest in their dynamic relationship are still rare. In empirical literature, there are a few studies employing "dynamically oriented" statistical analysis like vector autoregression [17] or a system of simultaneous equations [19]. A substantial exception is social media research, which has accumulated a significant body of work on the diffusion of protest information and behavior. However, for obvious reasons, the study of repression is problematic in an online environment.

There are at least three streams – quite different in their breadth of use – in the modelling of the protest-repression nexus. A number of studies have been conducted within the tradition of game theory (see e.g. [6]). Yet the capacities of game-theoretic models for the study of dynamics are seriously limited due to the special features of their formal apparatus.

Occasional attempts have been made in line with the system dynamics methodology. One recent example is [20]. Based on interesting ideas, this model is oversimplified: it includes only one dynamic variable. In general, their approach has two advantages in studying the protest-repression interplay: the models provide an opportunity to study the nuanced dynamics (in contrast to game theory) and they are – at least partly – analytically tractable. At the same time, being a macro level methodology, it does not allow examining micro-mobilization interactions.

The limitations of game theory and system dynamics are largely overcome in agent-based modelling (ABM), which combines complex dynamics with microfoundation approach [21]. Indeed, a considerable share of the existing protest-repression models have been developed within the ABM framework. The most influential tradition originates from Epstein's seminal model of civil violence [22]. The most important ideas of this and subsequent work – from the point of view of our study – are as follows.

Firstly, the transition of an individual (agent) from a passive state to an active ("rebellious") one depends on the states of other agents. In the original Epstein's specification, as well as in [23], the agent reacts to the behavior of other individuals within her spatial neighborhood – the number of lattice positions in all directions that the agent is able to inspect (so called "vision"). In other models, this principle can be implemented differently. For example, agents may be interconnected in networks [24]. In some models, additional selection mechanisms – such as homophily [25], group identity [26], or incomplete information [27] – may work. In the model presented in this paper, we stick to the simplest version of the agent's interconnection, dating back to seminal Granovetter's [28] work: every agent has complete information about the total number of protesters.

Secondly, the individual's decision to join the protest is based upon a threshold rule: switching between passive and active states occurs when the difference between the incentives to protest exceeds the constraints. Motives for participation can be formed by individual (e.g. personal hardships in the original model) and global (e.g. legitimacy of the regime) properties. Disincentives may be determined by personal characteristics (risk aversion) and, more importantly, by external risks - namely repression. To measure the latter Epstein used the probability of being arrested, calculated as a function of the cop-to-rebel ratio within the agent's neighborhood. It is influenced, among other parameters, by "cop density" - the fraction of law enforcement forces in the total population. Some replicas of his model introduce additional parameters, such as effectiveness in the military capacity [29], apply different forms of arrest probability function [30] etc.

One way or another, in the whole family of such models, repression affects only one side of the motivation-constraint balance. It increases the perceived cost of protest, - completely in line with the classical rational choice view. From the socio-psychological perspective, though, we must allow the possibility of an alternative effect: repression can provoke anger and outrage, thus contributing to the motivational side. This does not exclude, of course, the deterrent role of repression described above.

One of the most convincing attempts to take this duality into account was made by Siegel [31]. Though the main focus of this widely cited paper is the social network structure (with very promising findings), here we draw attention to the way in which the psychological response to repression is considered. Within Siegel's framework, repression is modeled by removing protesters from the network, thus eliminating both their direct participation and their influence on others via local network connections. The psychological impact is that those with whom the repressed were connected grow *either* angry *or* fearful. From a formal point of view, this means that *two different* specifications are needed: one with a positive effect on motivation (in our terms), the other with a positive effect on deterrence.

Yet, in reality, these bidirectional effects act simultaneously. And the solution of the protest-repression puzzle may not be completely reliable without directly taking this fact into account. In this paper, we develop a general design of such a model and examine its performance using numerical experiments and - supplementary - analytical investigation.

2. Model

The considered type of process is a multi-day street action, such as Euromaidan in Kyiv (21 November 2013 - 24 February 2014), Jasmine Revolution in Tunisia (18 December 2010 – 14 January 2011) etc. The key variable in the model is the number of protesters $P(t)$, measured in thousands of people without loss of generality. Here t is the day's number. Another important variable is the severity of repression against the protesters: $s(t) = [0, 1]$. It can be imagined, for instance, that $s = 0.1$ refers to a fine, while $s = 0.9$ constitutes a risk of physical injury or a long imprisonment.

Aiming at obtaining the dynamical equation of the model, we start from considering a sympathizer to the protest and analyzing this individual's motives to participation in this protest on a certain day versus non-participation, that is motive to action and motive to inaction.

The risk of suffering from repression is an obvious component of motive to inaction. Here the word "risk" refers to the exposure to something detrimental. The measure of risk is a quantitative value $\omega\left(s(t), q\left(P(t)\right)\right)$ called net risk [22]. It depends on the severity of repression $s(t)$ and the probability q of the individual to get hurt in case of participation. This probability, in turn, depends on the current number of participants so that it is low when the number of participants is high. We put $q(P) = e^{-P}$. Under this specification, the probability of getting hurt is approximately 0.95 if as little as 50 protesters turned out ($e^{-0.05} = 0.95$), and the probability is 0.0025 if there are 6000 protesters ($e^{-6} = 0.0025$).

For the net risk we put $\omega(s, q) = 1 - \exp(-100sq)$. This functional form means that even moderate repression constitutes a strong motive for non-participation if combined with high probability of punishment. Similarly, even a low probability of getting suffered is aversive if the repression is severe.

In this paper we assume that risk is the only component of the motive to inaction, thus $M_{inaction}(t+1) = \omega\left(s(t), q\left(P(t)\right)\right)$, that is

$$M_{inaction}(t+1) = 1 - \exp\left(-100 s(t) e^{-P(t)}\right).$$

This formula presumes that the individual estimates the net risk of participation on day *t*+1 basing on data from previous day.

Let us now proceed to the motive to action.

Following the modern developments of the psychology of protest, we employ the psychological antecedents of the decision-making as mediators between social factors and the individual's decision on whether to participate or not (today). The antecedents are anger *a*, efficacy belief *b*, and personal identification with the protest movement *d* [15].

The constant component of anger is the one that triggered the protest: $a_0 = const$. It may be caused, for instance, by election fraud or unpopular economic reform. The second component appears as a backlash against repression; the simplest specification of it is $a_1 = s$. Note that in this case only the existence and severity of repression matter, but not the individual probability of suffering from it. We put that individual anger is the mean of the two components: $a = (a_0 + s)/2$, $0 \le a \le 1$.

Efficacy belief "refers to perceived efficacy of an action in achieving the political goals of the movement" [15] and can by thought of as the perceived possibility of success of protesters. It depends on their current number:

$$b(P) = \frac{\exp\left(k(P - P_0)\right)}{1 + \exp\left(k(P - P_0)\right)}.$$

Here *k* and P_0 are positive constants. Efficacy belief equals 0.5 when the number of participants is equal to P_0. For our numerical experiments we take P_0=100 and $k = 0.01$. Under these values of parameters efficacy belief is approximately 0.39 when *P*=50 (thousand), and it is 0.95 when *P*=400.

The individual's identification *d*(*t*) with the movement depends in theory on the severity of repression, but for the sake of simplicity we consider it constant.

Our model combines these three psychological antecedents of decision-making in the motive to action as

$$M_{action}(t+1) = 0.5 a(t) b(t) \left(1 + d(t)\right),$$

so that $0 \le M_{action}(t) \le 1$. Using the above formulae, we get

$$M_{action}(t+1) = 0.25(1+d)\left(a_0 + s(t)\right)\frac{\exp\left(0.01P(t) - 1\right)}{1 + \exp\left(0.01P(t) - 1\right)}.$$

The difference between the motive to action and motive to inaction gives the total motive:

$$\psi(t) = M_{action}(t) - M_{inaction}(t)$$

According to the neurological model [32], the individual's political position is the sum of their attitude φ and the total motive ψ:

$$\lambda = \varphi + \psi(t).$$

Here attitude φ is the individual's long-term predisposition towards participation, which depends on the person's social experience and status, supposed to be developed before the commencement of the protest action and to remain constant over the whole course of it.

The individual attends the protest action on day *t* if their latent position is positive on that day. In terms of the model, the manifest position *p* = 1 if $\lambda(t) > 0$, that is $\varphi > -\psi(t)$. Similarly, the manifest position *p* = 0 (the individual does not attend the action) if $\lambda(t) \le 0$. Thus, latent position is a continuous scalar variable, while manifest position is a binary variable.

It follows from these definitions that the number of protesters is given by

$$P(t) = \int_{-\psi(t)}^{\infty} n(\varphi)\, d\varphi,$$

where *n*(φ) is the distribution of attitudes among individuals.

Specification of severity of repression as a function of time (and/or anything else) is the matter of the strategy of the government.

This completes the formulation of the model.

In what follows we assume the continuous uniform distribution of attitudes, that is

$$n(\varphi)=\begin{cases} N_0, & -1<\varphi<0 \\ 0, & otherwise \end{cases},$$

where N_0 is the total number of individuals.

3. Steady State under Constant Severity of Repression

Probably the main question about an impending protest, or uprising, or revolution is what is going to be the turnout at the end of it. In radical form, the question is whether the projected number of protesters is high enough to topple the government down.

Accordingly, this Section studies the number of protesters when $t \to \infty$.

Under the assumption of uniform distribution of attitudes made in the previous Section we have

$$P(t)=\int_{-\psi(t)}^{\infty} n(\varphi)\,d\varphi=\begin{cases} 0, & \psi(t)\le 0, \\ N_0\psi(t), & 0\le\psi(t)\le 1, \\ N_0, & \psi(t)\ge 1. \end{cases}$$

Considering only the case when some proportion of the population attends the protest (that is, leaving out situations $P(t)=0$ or $P(t)=N_0$ for some t), assuming constant severity of repression s and taking N_0 = 100 for the sake of definiteness, we obtain after some algebra that

$$\psi(t+1)-\psi(t)=F(\psi,s),$$

where

$$F(\psi,s)=0.25(1+d)(a_0+s)\frac{\exp(\psi(t)-1)}{1+\exp(\psi(t)-1)}-1+\exp\left(-100se^{-100\psi(t)}\right)-\psi(t).$$

Steady-state solution is given by $\psi(t+1)=\psi(t)$, that is $F(\psi,s)=0$. We considered the function $F(\psi,s)$ with parameters $d = a_0 = 1$, and different values of severity s. As an example, the graph for s = 2 is presented in Fig. 1.

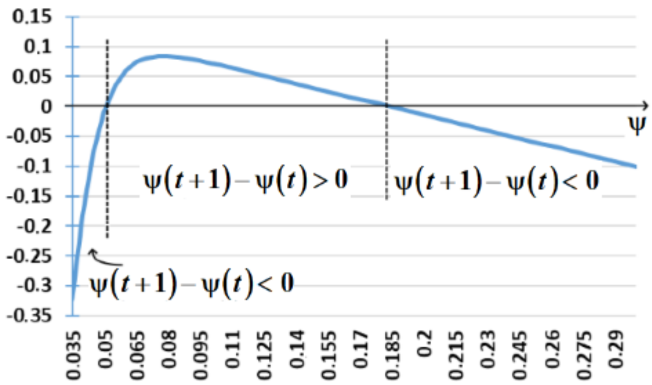

Figure 1: The graph of the function $F(\psi,s)$ with s = 2 (blue line)

There are two steady states, namely $\psi_1=0.051$ (unstable) and $\psi_2=0.184$ (stable). This means that:

- if on the first day of the protest the number of protesters is less than $N_0\psi_1=5.1$ (thousand people), then $\psi(t+1)-\psi(t)<0$ for each t, that is the turnout decreases from day approaching to zero,

- if on the first day of the protest the number of protesters exceeds $N_0\psi_1=5.1$, then the turnout approaches to the value $N_0\psi_2=13.4$ (thousand people).

Thus $N_0\psi_1=5.1$ can be thought of as the threshold the opposition needs to overcome in order to succeed in gathering big numbers. Once the threshold has been overcome, they ride the positive dynamics.

Considering different levels of severity, we obtained that both ψ_1 and ψ_2 are increasing functions of s. That is, more severe repression raises the threshold before the opposition, but overcoming this threshold allows them to achieve a greater turnout.

4. Numerical Experiment: Constant Severity and Stochastic Element in Attitudes

We test the model's key interactions by outlining several protest scenarios. We investigate the stationary number of protesters ($P_{t=\infty}$) and its dependence on the severity (s) of repression. We apply a combination of different designs: we calculate dynamical motivation $\psi(t)$ within the dynamical model, while attitude φ is individual for each actor in the sample.

Let there be a population of 100 attitudinally heterogenous citizens, so $\varphi_i \in (-1;0)$. The attitudes of individuals are uniformly distributed, and each individual's position is re-calculated at the beginning of each experiment. Therefore, we use the simple form of the Monte-Carlo method.

In all scenarios the system reaches stationary state after about 10 model days, but we let the experiment run for 100 model days. We record the number of protesters P(t) at t = 100. Every scenario consists of 1000 experiments, each with a fixed value of repression severity s set at t = 1. In other words, for this simplified experiment we assume that the government makes a single decision about repression severity on the first day of the protest event and then never deviates from that decision. We increase the value of s between experimental runs by increments of 0.1, beginning with 0 and ending with 1.

The sequence of events in the model unfolds as follows. It is supposed that at the onset of the experiment there are no protesters and no repressions ($P(0) = s(0) = 0$). We record each individual's attitude φ_i, then calculate the system's balance of motivation $\psi(t)$. Thus 'in the morning' of day t=1 each of the individuals makes their decision concerning whether to participate in this day's protest event. The individuals who decided to participate demonstrate their manifested position p = 1 by taking to the streets. We add up all the values of p to calculate the total number of protesters on day t = 1. On the same day the government carries out repressions of a set severity level against the protesters (zero-repression policy $s(1) = 0$ is also an option, which simply means there are no repressions). Next morning, each individual makes a decision about their participation in the protest at t = 2 based on their attitude, the number of protesters $P(1)$ and the severity of repression $s(1)$. The process continues until t = 100, at which point we record the number of protesters.

We analyse the experimental outcomes using descriptive statistics for values of P at different levels of repression severity. Fig. 2-4 show the distributions for s = 0, s = 0.4 and s = 0.9, respectively.

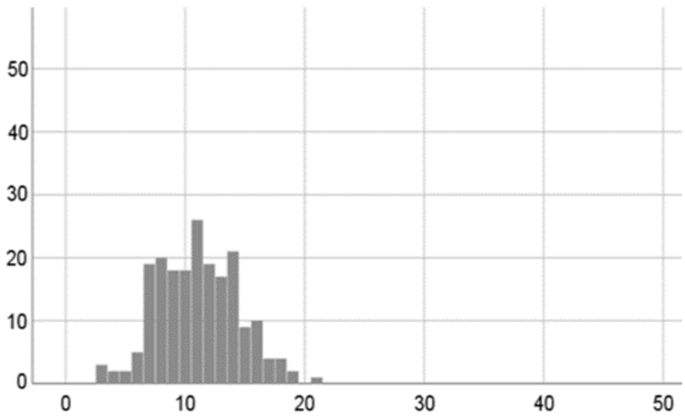

Figure 2: Distribution of protester numbers at t = 100 for s = 0

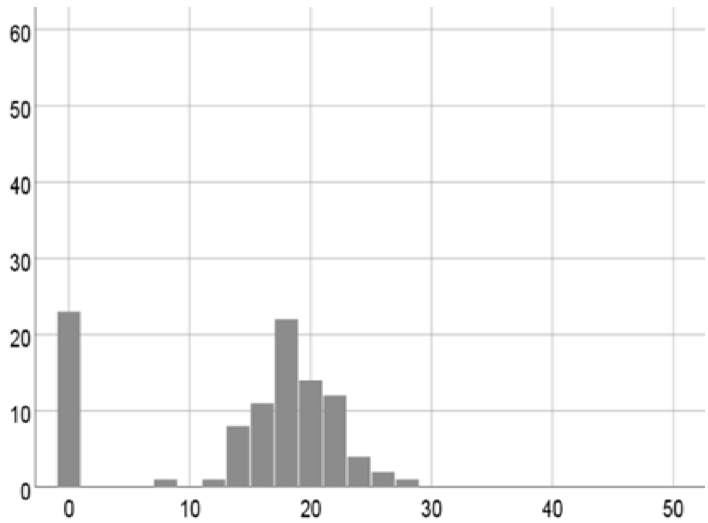

Figure 3: Distribution of protester numbers at *t* = 100 for *s* = 0.4

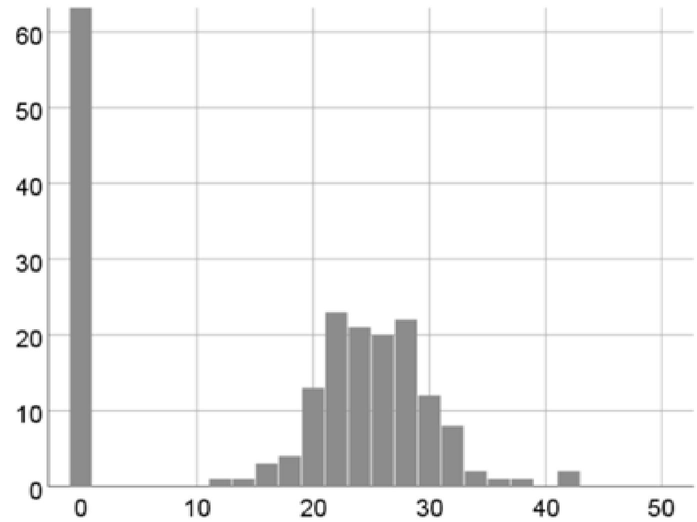

Figure 4: Distribution of protester numbers at *t* = 100 for *s* = 0.9

At zero repression, the protest level distribution is close to normal with a relatively small mean (about 11 out of 100 individuals), case minimums ranging from 3 to 21 and a standard deviation of 3.4. Of note is the absence of a zero equilibrium (although it is possible with a rare combination of individual positions): there is always a relatively small group of people whose willingness to participate outweighs the difference in motivation.

The distribution changes qualitatively at non-zero repression levels: there is a split in the distribution proportional in magnitude to repression severity. Fig. 2 and especially Fig. 3 show a pronounced stationary outcome with zero protesters which corresponds to repressions reaching their intended purpose.

However, in the cases when the repressions fail to coerce the population into compliance, we observe a significant increase in the number of protesters. Table I. demonstrates descriptive statistics for various levels of s: of note is that the maximum number of protesters increases monotonously with the increase in repression.

The results of the numerical experiment show that the model retains the qualitative causal mechanism introduced during specification: in accordance with our expectations and existing research, repressions demonstrate a complex interaction with protest activity. An increase in repression levels leads to a more pronounced division between two possible outcomes of a contentious political event: successful protest (up to a revolutionary change in government) and failed protest.

Table 1
Descriptive statistics of numerical results (constant severity)

S	Mean	median	St. dev.	min	max
0	11.08	11.00	3.39	3	21
0.1	11.63	12.00	5.16	0	22
0.2	11.91	13.00	6.23	0	27
0.3	12.46	14.00	6.93	0	28
0.4	12.74	15.00	7.92	0	26
0.5	13.98	17.00	8.29	0	27
0.6	15.45	18.00	8.81	0	30
0.7	16.33	19.00	9.79	0	35
0.8	16.96	21.00	10.17	0	37
0.9	16.93	22.00	11.80	0	34

5. Numerical Experiment: Adaptive Severity and Stochastic Element in Attitudes

In this Section we suppose the severity to be the increasing function of the number of protesters from the previous day. The underlying idea is that the government decides to heighten severity of repression if faces a greater number of protesters. For the sake of definiteness, we take the following specification:

$$s(t) = \left[1 + \exp\left(-k_S P(t-1) + b\right)\right]^{-1}.$$

Here the parameter k_S characterizes the "asymmetry" of government's forcible response to the mass action. Relatively small values of k_S correspond to restrained policies when the government exercises low-severity repression while the number of protesters is not too large. Greater values of k_S correspond to harsher policies. In our numerical experiments k_S was given values 0; 0.1; 0.2; … 1.

First, consider the severity of repression as a function of k_S. Figure 5 presents the average (over Monte Carlo realizations) of maximum (over time) value of repression for various values of the parameter k_S.

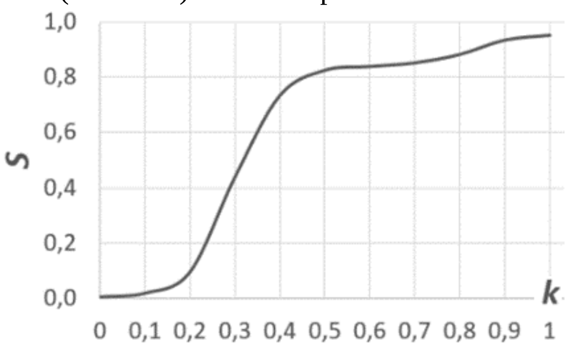

Figure 5: The average maximum value of repression for various values of *k*

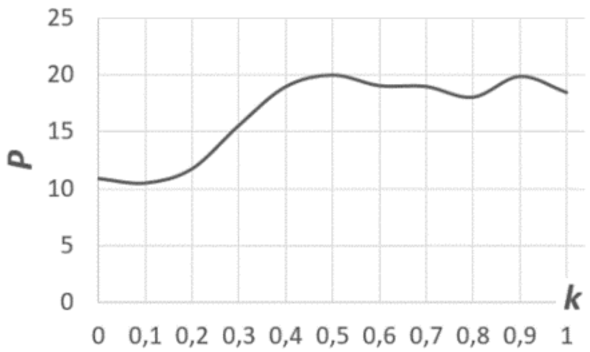

Figure 6: The average number of protesters for various values of *k*

Table 2
Numerical results (adaptive severity)

k	*P*(average)	*P*(max)	*S*(average)	*S*(max)
0	10.91	10.96	0.01	0.01
0.1	10.5	10.56	0.02	0.02
0.2	11.75	11.93	0.09	0.1
0.3	15.57	16.15	0.41	0.44
0.4	18.99	20.01	0.69	0.73
0.5	20.02	21.16	0.78	0.82
0.6	19.09	20.73	0.77	0.84
0.7	19.01	20.82	0.75	0.85
0.8	18.06	20.16	0.72	0.88
0.9	19.9	21.73	0.77	0.93
1	18.49	20.44	0.75	0.95

The number of protesters depends on k nonmonotonously (Fig. 6, Table 2). However, the big picture is that the less self-restrained is the government, the greater is the number of protesters.

Note that the distribution of the average number of protesters under various values of k could hardly be guessed without modeling.

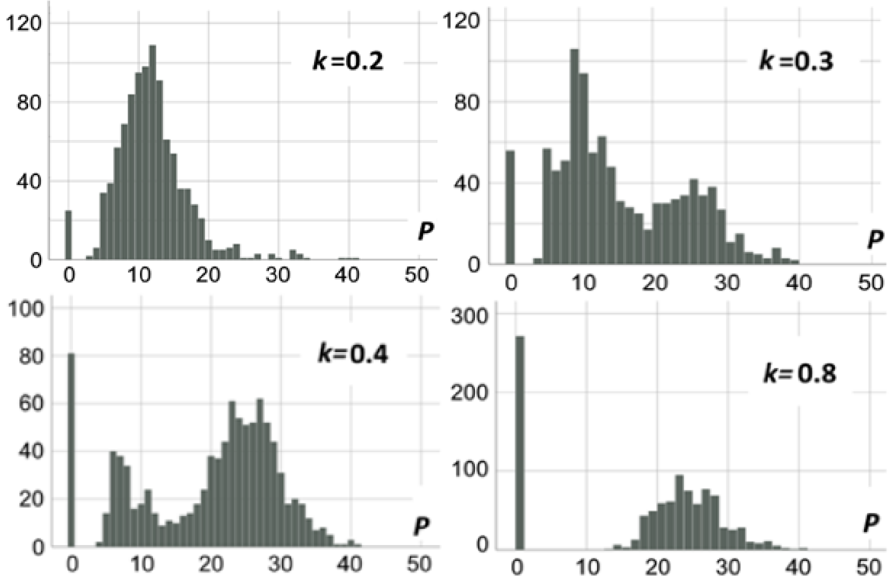

Figure 7: The distribution of the average number of protesters

If the government pursues a restrained policy (k is low), then the protest is quite predictable and limited. However, if the government acts harshly, the process becomes twofold: it will either grow strong or become fully suppressed. A small difference in the distribution of attitudes can be decisive between these two scenarios.

6. Conclusion

The dynamic model of the protest-repression interaction, which we present in this paper, makes several contributions to the literature. It provides an explanation for the mixed results of studies that examine how repressions affect the possibility of the protest backlash. We show, on the one hand, that an increase in repression levels leads to a more pronounced division between two possible outcomes of a contentious political event: successful protest and failed protest. On the other hand, the model highlights the importance of the intensity of the government's repressive reaction to protests. The more disproportionate ("nervous") this reaction is, the less stable the situation becomes. The latter means that the protest will either be suppressed or become extremely massive, but it is unlikely to remain moderate. Both findings are qualitatively similar and point towards a general conclusion: the suppression of protest diminishes the predictability of its further course.

We offer several new model solutions to bring simulation dynamics closer to real life. Most importantly, we found a way to simulate both the positive and negative effects of repression on participation within the same model specification. Next, the model endogenizes not only the dynamics of the number of protesters, but also the intensity of repression. Finally, we demonstrate practical tools for modeling a wide range of individual behavior motives.

Prospects for the further development of the model are seen, primarily, in the complication of agent interaction. A promising strategy is to add a network structure to existing mechanisms of agents' decisions about participating in protest events. Experiments with distribution shapes of individuals' attitudes can also bring interesting results.

7. Acknowledgements

The study was supported by Russian Foundation for Basic Research (project 18-011-01134).

8. References

[1] M. Lichbach, Deterrence or escalation? The puzzle of aggregate studies of repression and dissent, Journal of Conflict Resolution, vol. 31 (1987), pp. 266–297.
[2] A. Honari, From 'the effect of repression' toward 'the response to repression', Current Sociology, vol. 66(6), 2018, pp. 950–973.
[3] P. Regan, E. Henderson, Democracy, threats and political repression in developing countries: Are democracies internally less violent?, Third World Quarterly, vol. 23(1), 2002, pp. 119–36.
[4] J. Sutton, C. Butcher, I. Svensson, Explaining political jiu-jitsu institution-building and the outcomes of regime violence against unarmed protests, Journal of Peace Research, vol. 51(5), 2014, pp. 559–573.
[5] B. Slantchev, K. Matush, The Authoritarian Wager: Political Action and the Sudden Collapse of Repression, Comparative Political Studies, vol.53 (2), 214–252 (2020).
[6] J. Pierskalla, Protest, deterrence, and escalation: The strategic calculus of government repression, Journal of Conflict Resolution, vol. 54(1), 117–145 (2010).
[7] S. Bell, A. Murdie, The apparatus for violence: Repression, violent protest, and civil war in a cross-national framework, Conflict Management and Peace Science, vol. 35(4), 336–354 (2018).
[8] B. Christensen, J. Groshek, Emerging media, political protests, and government repression in autocracies and democracies from 1995 to 2012, International Communication Gazette, (January 2019) doi:10.1177/1748048518825323.
[9] J. Jasper, Constructing Indignation: Anger Dynamics in Protest Movements, Emotion Review, vol. 6(3), 208–213 (2014).
[10] J. Stekelenburg, B. Klandermans, The Social Psychology of Protest, Current Sociology, vol. 61 (5–6), 886–905 (2013).
[11] K-D. Opp, W. Roehl, Repression, micromobilization, and political protest, Social Forces, vol. 69(2), 521–524 (1990).
[12] K. Rasler, Concessions, repression, and political protest in the Iranian revolution, American Sociological Review, vol. 61(1), 132–152 (1996).
[13] J. Drury, S. D. Reicher, Collective action and psychological change: The emergence of new social identities, British Journal of Social Psychology, vol. 39(4), 579 – 604 (2000).
[14] M. Soares, M. Barbosa, R. Matos, S. Mendes, Public Protest and Police Violence: Moral Disengagement and Its Role in Police Repression of Public Demonstrations in Portugal, Peace and Conflict: Journal of Peace Psychology, vol. 24, 27–35 (2018).
[15] A. H. Ayanian, N. Tausch, How risk perception shapes collective action intentions in repressive contexts: A study of Egyptian activists during the 2013 post-coup uprising, British Journal of Social Psychology, 55(4), 700-721 (2016).

[16] R. David, M. Ward, They Dance Alone: Deaths and the Disappeared in Contemporary Chile, Journal of Conflict Resolution, vol. 34, 449-75 (1990).
[17] S. Carey, The dynamic relationship between protest and repression, Political Research Quarterly, 59(1), 1–11 (2006).
[18] C. Sullivan, C. Loyle, C. Davenport, The coercive weight of the past: Temporal dependence and the conflict–repression nexus in the Northern Ireland ‘‘Troubles’’, International Interactions, vol. 38(4), 426–442 (2012).
[19] Ph. Hultquist, Is collective repression an effective counterinsurgency technique? Unpacking the cyclical relationship between repression and civil conflict, Conflict Management and Peace Science, vol. 34(5), 507–525 (2017).
[20] J. Lang, H. De Sterck, The Arab Spring: A simple compartmental model for the dynamics of a revolution. Mathematical Social Sciences , vol. 69, 12-21 (2014).
[21] E. Bonabeau, Agent-based modeling: Methods and techniques for simulating human systems, Proceedings of the National Academy of Sciences, vol. 99 (s. 3), 7280-7287 (2002).
[22] J.M. Epstein, Modeling civil violence: An agent-based computational approach, Proceedings of the National Academy of Sciences, 99 (s. 3), 7243-7250 (2002).
[23] D. Braha, Global Civil Unrest: Contagion, Self-Organization, and Prediction, PLoS ONE, vol. 7(10), e48596 (2012).
[24] C. Lemos, Agent-Based Modeling of Social Conflict From Mechanisms to Complex Behavior, Springer International Publishing, Switzerland (2018).
[25] M. Makowsky, J. Rubin, An Agent-Based Model of Centralized Institutions, Social Network Technology, and Revolution, PLoS ONE, vol. 8(11), e80380 (2013).
[26] J. Kim, R. Hanneman, A computational model of worker protest, Journal of Artificial Societies and Social Simulation, vol. 14(3), (2011).
[27] A. Little, Communication Technology and Protest, The Journal of Politics, vol. 78(1), 152-166 (2016).
[28] M. Granovetter, Threshold Models of Collective Behavior, The American Journal of Sociology, vol. 83 (6), 1420-1443 (1978).
[29] A. Moro, Understanding the Dynamics of Violent Political Revolutions in an Agent-Based Framework, PLoS ONE, vol. 11(4): e0154175 (2016).
[30] M. Fonoberova, V. Fonoberov, I. Mezic, J. Mezic, P. Brantingham, Nonlinear Dynamics of Crime and Violence in Urban Settings, Journal of Artificial Societies and Social Simulation, vol. 15(1), 2012.
[31] D. Siegel, When does repression work? Collective action and social networks, Journal of Politics, vol. 73(4), 993–1010 (2011).
[32] A. Petrov, O. Proncheva: Modeling Propaganda Battle: Decision-Making, Homophily, and Echo Chambers. Artificial Intelligence and Natural Language. Communications in Computer and Information Science, vol. 930. 197-209 (2018).