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Does Non-violent Repression Have Stronger Dampening Effects than State Violence? Insight from an Emotion-Based Model of Non-violent Dissent

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Abstract

The effects of repression on dissent are debated widely. We contribute to the debate by developing an agent-based model grounded in ethnographic interviews with dissidents. Building on new psychology research, the model integrates emotions as a dynamic context of dissent. The model moreover differentiates between four repression types: violence, street blockages, curfews and Facebook cuts. The simulations identify short-term dampening effects of each repression type, with a maximum effect related to non-violent forms of repression. The simulations also show long-term spurring effects, which are most strongly associated with state violence. In addition, the simulations identify nonlinear short-term spurring effects of state violence on early stage dissent. Such effects are not observed for the remaining repressive measures. Contrasting with arguments that violence deters dissent, this suggests that violence may fuel dissent, while non-violent repression might suppress it.

The repression–dissent nexus

The relationship between state repression and political dissent has been debated widely. Much research shows that repression is a common response to dissent (Chenoweth et al. 2017; Combes and Fillieule 2011; Davenport 2007; Lichbach 1987; Tilly 1978), especially in non-democratic settings (Beiser-McGrath 2019; Carey 2006; Combes and Fillieule 2011; Keremoğlu et al. 2021). However, the effects of repression on dissent remain unclear. Some argue that repression increases dissent (Dornschneider and Henderson 2016; Francisco 1995, 1996, 2004; Hafez 2003; Toft and Zhukov 2012), whereas others say that repression

dampens dissent (Davenport 2015; Gurr 1970; Lichbach and Gurr 1981; Muller and Weede 1990). Recent studies suggest that the relationship between repression and dissent is reciprocal (Carey 2006) or endogenous (Ritter and Conrad 2016).

We contribute to this literature by developing an agent-based model (Axelrod 1997a; Schelling 1971) that explores possible state–dissident interactions arising from individual actions and interactions. This individual-based approach adds new, micro-level insight into the effects of state repression on dissent, which have been explored extensively by large-N studies of aggregate data at the national level (e.g. Carey 2006; Muller and Weede 1990). Our analysis builds on the emerging literature applying agent-based modelling (ABM) to examine state–dissident interactions (Akhremenko and Petrov 2020; Dacrema and Benati 2020; Epstein 2012; Moro 2016), consistent with the broader ABM literature on related subjects, such as intergroup conflict (Bhavnani et al. 2014), global polarization (Axelrod 1997b), the diffusion of democracy (Elkink 2011) or dissent within organizations (Garner 2016). Our model advances this research by integrating findings from new ethnographic research on political dissent.

The model includes emotions, which are known to influence protest behaviour (Goodwin 2001; Goodwin et al. 2013; Jasper 2014; Pearlman 2013; Spring et al. 2018; van Zomeren et al. 2008; Young 2019) but not yet represented in existing agent-based (see above) or rational choice models (e.g. Beiser-McGrath 2019; Rasler 1996) of state–dissident interactions. Recent findings (Dornschneider 2021a) show that decision-making on non-violent dissent relies on emotion-based reasoning, and involves the hot and cool cognitive system (Kahneman 2011; Metcalfe and Mischel 1999). The hot system is known as the 'go' system, in which emotions motivate fast decisions that embrace protest, whereas its cool counterpart constitutes a 'know' system, in which strategic and self-controlling considerations encourage slow decision-making, rejecting protest participation. To capture these features, our model simulates protest behaviour based on dynamic emotional levels of the population, which change related to the availability of protest knowledge.

In the simulations, the levels of emotions identify four protest conditions, representing different levels of criticality. These are emotionally cool conditions, which result in few or no protesters being in the street ('low'); conditions in which emotional levels 'warm up', and people start to protest ('critical'); increasingly 'warm' conditions in which protest levels rise and potentially reach maximum levels ('supcritical'); and hot, emotion-laden conditions in which masses are on the streets ('high'). These emotion-based conditions provide a novel and dynamic context of state–dissident interactions, adding micro-level insights to well-studied structural contexts, including regime types (e.g. Carey 2006; Daxecker and Hess 2013; Gupta et al. 1993), economic conditions (e.g. Maher and Peterson 2008) or dissident networks (e.g. Berman 2021; Grimm and Harders 2018; Siegel 2011). Consistent with threshold theories of protest, the identified conditions represent a social tipping process, in which protest size increases related to the number of people in the street (Granovetter 1978; Kuran 1991; Lohmann 1994; Noelle-Neumann 1974; Wiedermann et al. 2020). Rather than focusing on one threshold at which protest begins to spread dramatically, however, the emotional context of our model also captures earlier stages in the mobilization process and some environmental factors.

Our model explores the possible effects of four types of repression: state violence targeting ongoing protest, and non-violent interventions on the protest infrastructure in the form of street blockages, curfews and Facebook cuts. These forms of repression are known to play an important role in protest movements (e.g. Berman 2021; Dave et al. 2020; Gillham et al. 2013; Little 2016) and are widely believed to have been key to mobilization in the Arab Spring, the main subject of the qualitative study informing our agent-based model (cf. Howard et al. 2011; Josua and Edel 2015; Lawrence 2017; Lynch 2011). As shown in the methods section, each of these forms of repression can readily be integrated into ABM simulations as specific governmental behaviours targeting protest movements as they unfold. Although research acknowledges the importance of differentiating between varying types of repression (Davenport 2010; Earl 2011; Piazza 2017), the selected repression types have not yet been explored comparatively. In addition, our model differentiates between their short- and long-term effects, which may vary (e.g. Rasler 1996; Rozenas et al. 2017; Zhukov and Talibova 2018).

The findings on short-term effects are consistent with theories on the dampening effect of repression, according to which repression decreases dissent (e.g. Davenport 2015; Lichbach 1987; Moore 1998; Zhukov and Talibova 2018). The simulations identify negative short-term effects related to each repression type examined by the analysis. In the model, offline blockages of the protest infrastructure are associated with the maximum short-term dampening effect and state violence displays both dampening and spurring effects in critical conditions, suggesting that its short-term effects are non-linear and may fuel protest movements as they are taking off. Contrasting with widespread applications of state violence, the findings suggest that non-violent repression might have stronger short-term dampening effects, whereas state violence applied in early protest stages could involve backfiring effects.

The simulations also identify possible long-term effects of each repression type, which are especially strong related to state violence. The identified effects are consistent with the backlash literature, according to which repression fuels dissent (e.g. Dornschneider and Henderson 2016; Francisco 1995, 1996; Hafez 2003; Toft and Zhukov 2012): each repression type is associated with a long-term spurring effect, suggesting that spurring happens over time, after repression has ended (cf. Combes and Fillieule 2011; Rasler 1996). These findings complement substitution models of dissent, according to which dissidents under increasing repression switch from non-violent to violent means (e.g. Lichbach 1987; Moore 1998). Our findings suggest that non-violent dissidents faced with state violence may stay true to their non-violent approach in the long term, increasing their non-violent activity at a later point in time.

Emotions

Emotions are subjective experiences that arise in the context of certain situations and involve action tendencies (Frijda 1988). While the literature on protest shows that emotions play a crucial role that both fuels and deters dissent (Goodwin et al. 2013; Jasper 2014; Pearlman 2013; Spring et al. 2018; van Zomeren et al. 2008; Young 2019), those findings have not yet been integrated by the literature on the state–dissident nexus.

The protest literature emphasizes the importance of negative emotions during the build-up and spread of non-violent dissent. In particular, anger is considered to contribute to mobilization processes (e.g. Ayanian and Tausch 2016; Jasper 2014; van Zomeren et al. 2008), as well as frustration (e.g. Davies 1962; Gurr 1970) and moral outrage (e.g. Goodwin et al. 2013; Spring et al. 2018). At the individual level, these emotions arise from perceptions of injustice among the members of disadvantaged social groups (van Zomeren et al. 2008). At the societal level, they are associated with relative deprivation in the distribution of power and wealth (Chenoweth and Ulfelder 2017; Davies 1962; Gurr 1970; McAdam et al. 2001).

Related studies in the social sciences link state repression to large-scale grievances that carry the potential of uniting segments of societies to engage in dissent, such as popular uprisings, violent attacks or civil wars (e.g. Goodwin 2001; Gurr 1970). Related psychology research on dissent does not typically conceptualize repression as a particular type of perceived injustice. Due to its threatening and damaging nature, however, repression carries a great potential to inflict injustice, possibly even beyond that of known structural or incidental disadvantages (cf. van Zomeren et al. 2008). The following study bridges these research fields by connecting repression to the actions and interactions of individuals, arising from the emotional climate in a given society.

Fear is another key emotion associated with protest behaviour. Research on protest (Pearlman 2013; Young 2019), rational choice (e.g. Lichbach 1987) and social networks (e.g. Amos et al. 2020) highlights fear's negative impact on protest behaviour. State repression plays a crucial role in fear-related dampening of protest. It is believed to induce fear in potential dissidents, thus deterring them from joining resistance movements. Theoretical models of the state–dissident nexus often assume such a role (e.g. Lichbach 1987), whereas a recent field experiment has provided empirical evidence from an authoritarian context (Young 2019). The following study integrates these findings by linking repression to emotional levels among the target population, which are in turn associated with protest behaviour.

Our agent-based model is developed from new research on dissident reasoning (Dornschneider 2021a). This research finds that repression may fuel political dissent through positive emotions (Finding 1) that strengthen and widen action-oriented thinking (Fredrickson 2001). Specifically, dissident decision-making is connected to positive emotions of solidarity with the victims of state repression, hope that non-violent dissent will bring down the repressive regime, courage to face repressive state authorities, as well as national pride. This finding suggests an emotional channel through which repression may support risk-embracing decision-making that spurs the mobilization process, which we include in our model.

Our model also integrates the new finding (Dornschneider 2021a) that individuals refrain from participating in non-violent dissent based on deliberations regarding their safety (Finding 2). Rather than primarily reacting to emotions of fear, individuals are found to carefully evaluate the threat of repression, and the associated costs of dissident behaviour. This finding is consistent with studies showing that cognition and emotions interact with each other (Lazarus 1982; Lerner and Keltner 2001), and that emotions are more than simple reflexes disconnected from thinking.

Our model moreover integrates the finding (Dornschneider 2021a) that the behaviour of others is the main source of emotions (Finding 3). This finding is consistent with social contagion and threshold theories of protest (see above) and new conceptualizations of protest cycles (Chang and Lee 2021), according to which non-violent dissent spreads based on the protest behaviour of others. While contagion models emphasize the negative role of fear (Kuran 1991; Noelle-Neumann 1974), which prevents people from joining unless a large number of protesters are on the street, the aforementioned new research emphasizes the role of positive emotions. Our model bridges these findings by introducing an emotional context that integrates both positive and negative emotions.

State violence, protest space, curfews and social media

The literature has identified complex effects of diverse forms of repression (Earl 2011). In the following analysis, we investigate the effects of four repression types that were observed by the dissidents we interviewed during the Arab Spring (Finding 4): state violence, street blockages, curfews and Facebook cuts. This focus helps to disentangle the varying effects of repression by examining repression types rather than structural contexts. It also contributes new insight into the particular effects of these repression types, which have hitherto been limited, as outlined in the following paragraphs.

State violence is associated with negative effects, including dampening (Davenport 2015; Lichbach 1987; Moore 1998; Zhukov and Talibova 2018) and pre-empting (Beiser-McGrath 2019; Danneman and Ritter 2014; De Jaegher and Hoyer 2019; Dragu and Przeworski 2019; Regan and Henderson 2002; Ritter and Conrad 2016; Sullivan 2016), as well as positive spurring (Dornschneider 2010; Finkel 2015; Francisco 2004) or 'vengeance' effects (Jaeger and Siddique 2018). Positive effects have been related to low or medium levels of state violence targeting early stage protest, whereas dampening effects have been related to increasing state violence against continued protest (Bell and Murdie 2018; Gurr 1970; Lichbach 1987; Lichbach and Gurr 1981; Muller and Weede 1990). The following analysis identifies possible spurring effects of both low and high levels of violence against early stage protest. It also shows that these effects can occur in both the short and long term. The analysis moreover shows that non-violent repression types can have stronger dampening effects than state violence. This suggests that violent repression may deter dissent less than commonly believed.

Research on protest space shows that control over streets creates shifts in the relative power of state and dissident actors (El-Ghobashy 2011; Zajko and Béland 2008). Road blockages and hard zones controlled by the state limit protest space and curb dissent (Gillham et al. 2013).[1] Consistent with this literature, the following analysis identifies dampening effects of road blockages in most contexts, but adds that this type of repression may have long-term spurring effects in critical conditions when protest becomes visible. Curfews have been related to both dampening and spurring effects. Crime-related research shows that they can significantly reduce gang violence (Fritsch et al. 1999) and youth crime rates (McDowall et al. 2000). Research on COVID-19 and the Black Lives Matter Movement confirms such dampening effects, but finds that people stay at home in settings with and

without curfews (Dave et al. 2020: 23). By contrast, conflict studies suggest that curfews are 'counter-productive' (Campbell and Connelly 2003: 343) and associated with hidden forms of resistance (Junaid 2020). The following study adds to this literature by showing that curfews have mostly dampening effects on dissent. In critical protest conditions where dissent becomes visible, curfews may be associated with long-term spurring effects.

Social media has a positive effect on dissent (Eltantawy and Wiest 2011; Howard et al. 2011; Little 2016; McGarty et al. 2014) because it enables people to share information about protest logistics (Little 2016) and provides alternative information contrasting the state narrative (Kirkizh and Koltsova 2021; Williamson and Malik 2020). State interventions on social media could be expected to have a dampening effect, as suggested by studies on media censorship that show that the consistent removal of alternative information over time curtails collective action (Chen and Yang 2019; King et al. 2013). The following analysis complements this literature by simulating the effects of Facebook cuts during and after dissent, finding only little support for a dampening effect. Facebook cuts may spur dissent in the long term, if they are performed in critical conditions where protest becomes visible. By contrast, the analysis finds that offline interventions on the protest infrastructure, such as curfews and street closures, have stronger negative effects on dissent.

The repression context

The following simulations investigate repression effects in a setting constructed from a particular case, namely the Egyptian and Moroccan Arab Spring. As such, this study addresses contextual features that have been examined by the literature to better account for the various effects of repression on dissent: political institutions, economic conditions and prior repression. Specifically, our setting is characterized by authoritarianism, high levels of poverty and a history of repression.

Constructed from interviews with dissidents, our model addresses institutional features via repression types that were observed in the Arab Spring.[2] Repression is often associated with authoritarian institutional settings (Beiser-McGrath 2019; Carey 2006; Combes and Fillieule 2011). In autocracies, it is believed to have dampening effects, whereas repression in democratic settings has been linked to spurring effects (Carey 2006; Daxecker and Hess 2013; Gupta et al. 1993). The following analysis complements this literature by providing evidence for both spurring and dampening effects within a setting modelled based on an authoritarian environment. The analysis suggests that dampening versus spurring effects can depend on the type of repression, rather than the institutional context.

Based on our interviews, our model moreover addresses economic conditions through employment levels, which were found to be a major factor motivating non-participation in dissent (Finding 5). This finding is consistent with grievance theories (Cederman et al. 2011; Davies 1962; Gurr 1970; Pfaff 2020; cf. Shadmehr 2014), according to which protest movements rely on perceptions of relative deprivation in the distribution of wealth and power. Unemployment in particular has been highlighted as a push factor of dissent (e.g. Della Porta 2008; Walker and Mann 1987). The following analysis shows that in an environment with a certain

level of grievances associated with employment, the dampening and spurring effects of repression can be differentiated through violent as opposed to non-violent repressive means.

Our model focuses on protest dynamics as they unfold over time. This focus adds to the existing, but inconclusive, research findings on the short- and long-term consequences of repression, which contain evidence for both positive (Rasler 1996) and negative (Zhukov and Talibova 2018) long-term repression effects. Recent research highlights the magnitude of repression, suggesting that long-term dampening effects are stronger when related to an 'iron-fist' strategy, but weaker related to a 'velvet-glove' strategy (De Jaegher and Hoyer 2019). Other studies describe the relationship between repression and dissent as reciprocal or endogenous (Carey 2006; Ritter and Conrad 2016). The following analysis adds to this literature by linking both short- and long-term spurring effects to violent as opposed to non-violent repression. It suggests that spurring is related to repression type, finding that increasing state violence is associated with spurring effects in both the short and long term, whereas the remaining measures are more related to dampening effects.

Agent-based modelling

ABM[3] is a computer simulation approach that explores social interactions based on the actions and interactions of individuals. In an agent-based model, each individual is represented by a separate entity, called an agent. Each agent has its own characteristics and behaviour, which define how the agent can act in a simulation. When the simulation is run, the agents act in parallel. That means that they interact with each other, depending on their specific state, knowledge and situation in the simulation. Given this set-up, ABM represents the micro-level dynamics of social interactions, based on the specific characteristics of individuals – something that often remains overlooked in the study of macro-level outcomes. The macro outcomes of these can then be systematically explored.

Understanding what has happened in a complex simulation can be hard, but it is open to indefinite inspection and experimentation. In this article, we focus exclusively on the effects of state repression on non-violent dissent. As such, our main focus lies on the relationship between dissident behaviour and repressive state behaviour. In our model, the agents are specified based upon empirical observations of individuals in a repressive setting. Our model environment also integrates some empirically observed features, most importantly an emotional context, as well as various other features, described below. The detailed findings complement existing studies of the state–dissident nexus by providing new, micro-level insights into the social tipping processes underlying mass mobilization under various conditions of state repression.[4]

ABM has a number of crucial advantages for studies of the state–dissident nexus: (1) It relates the micro-level (the cognition and actions of the agents) to the macro-level outcomes, allowing this relationship to be better understood; (2) it allows the modelling of the agents' behaviour to be based on any decision-making pattern; (3) it permits differing rather than uniform behaviour of agents depending on their different social, temporal and geographic contexts; and (4) it integrates a variety of

kinds of evidence, such as micro-level accounts of decision-making, evidence about social networks and macro-level characterizations of outcomes.

The emerging literature applying ABM to studies of the state–dissident nexus has made important contributions, identifying varying outcomes of revolutions (Moro 2016) and contentious politics (Akhremenko and Petrov 2020), basic dynamics underlying rebellions, populism and radicalization (Dacrema and Benati 2020), and complex dynamics related to decentralized rebellion and inter-ethnic civil violence (Epstein 2012). Drawing on new research on emotions, the following application offers new insight into the dynamics underlying the spreading of dissent. The findings facilitate the differentiation between dampening and spurring effects of repression, and the formulation of more fine-grained hypotheses to better understand the occurrence of these opposing effects.

While ABM can be used for many different purposes (Edmonds et al. 2019), our study explores the possible macro outcomes that result from implementing behaviours based on qualitative interview accounts, following Scott Moss and Bruce Edmonds (2005). This theoretical exploration of the model supports and makes precise hypotheses concerning how dissent might build or fade in light of the situation and the actions of the government. Although the model displays plausible patterns, future studies are needed to validate these empirically.

Model description
Social and emotional processes
The model contains two main processes based on which agents engage in dissent, capturing the role of positive emotions (Findings 1 and 2) and protest behaviour of others (Finding 3). The first process refers to changing movements of the agents in the model space – that is, between the locations, of streets, the square or a home (see below, 'protest space'). The second is a social contagion process concerning the emotions discussed above. This is a threshold-contagion process, in which emotions spread between individuals as they move across the model space. In each location, the emotional levels of individuals increase to match that of the average in the location. If the average is below that of an individual, nothing happens.

The model has background emotion dynamics that represent the wider emotional characteristics of the population and that control the processes that affect emotions for reasons that are external to those in the model. The background emotion dynamics are modelled by two parameters, namely 'av-wake-dampening' and 'wake-sd'. Both 'av-wake-dampening' and 'wake-sd' effect the dynamics and vary between 0 and 1. 'av-wake-dampening' is how fast emotions fade in the population on average from one day to the next. A value of 0 would mean all emotions of the previous day had dissipated, a value of 1 would mean that none had dissipated. 'wake-sd' is the variation in this dissipation between citizens. A value of 0 means all citizens dampen their emotions equally quickly. Higher values mean that this dampening can be higher or lower between different citizens. The values chosen for these two parameters during initialization turn out to be crucial for the position of critical tipping points. High levels of emotion in the population and variation between individuals tend to result in large numbers

protesting via the interactions modelled. Table 1 provides the related formula; the Online Appendix provides visualizations.

The emotional level of individuals can increase during the simulation. These increases depend on individuals' location in the simulation described below (see under 'protest space'). If an individual's emotional level is below that of the average of individuals in the same location, then it is moved up to the average (Finding 3). In addition, knowledge of state violence (if applied) can increase an individual's emotional level. Table 1 and Figure 1 provide an overview.

During the simulation, the emotional levels of individuals translate into behaviour in direct comparison with their safety considerations. This design represents the findings of the qualitative analysis, according to which two contrasting cognitive processes are associated with protest behaviour: people refrain from protest based on cool cognitive concerns for their safety (Finding 2), but join protest based on hot cognitive processes involving emotions (Finding 1). In the simulations, this is captured by the agents' movement being dependent on their emotional levels exceeding safety concerns. Table 1 shows the decision-making procedures for individual agents to move. The safety parameter is introduced below.

Other parameters

The remaining parameters are developed from the empirical findings outlined above. Their initial values were selected to represent the real situation as closely as possible. The main reference was Egypt, where many of the empirical data underlying the simulation were collected. Figure 1 gives an overview, including protest space.

The main motivator related to an agent staying away from protest is modelled by a parameter capturing concerns about safety, namely 'av-safety-prop' (Finding 2). This parameter can be set between 0 and 1 in the initialization process, and is subsequently assigned to individuals based on a random normal distribution in the simulation (with this average). The higher the individual's safety concern, the lower their protest likelihood. Their protest likelihood is estimated in a comparison between their emotional level and safety concerns, where their emotional level needs to be greater than their concern for safety to trigger protest behaviour. In the following simulations, the parameter is initialized at a high value of 0.95. This value is based on reports in the Egyptian newspaper *Masr al Youm*, according to which 257,050 people of the 82.8 million population participated in protest in Egypt in the year preceding the Arab uprisings 2010 (Gunning and Baron 2014: Appendix).

Another motivator related to an agent's protest behaviour is modelled by a parameter representing the employment level of the population, namely 'employment%' (Finding 5). This parameter takes values between 0 and 100 and is set at a certain value in the initialization stage. In the simulation, individuals who are unemployed are more likely to participate in protest during the day, whereas individuals who have employment are equally likely to join the protest in the evening. In the following simulations, employment% was initialized at 88. This value is based on reports by the Central Agency for Public Mobilization and Statistics, according to which Egypt was reported to have between 12.4% and 11.9% of unemployment in 2011 (*Egypt Independent* 2021).

Table 1. Description of the ABM, Excluding Initial Values

Agent	Condition	Action
Mornings only		
wake		
Citizen		know-of-protest is off
		know-of-attack is off
		protesting is off
		attacked is off
		stay-home is off
		$e_i = e_i \cdot N(\mu_d, \ \sigma_d)$, truncated at [0,1]
Facebook		show-protest is off
		show-attack is off
All time periods		
move		
Citizen	attacked is on	**go home**
	at home *and* not attacked *and* not stay-home *and* employed *and* evening	**go to street**
	at home *and* not attacked *and* not stay-home *and* not employed *and* (daytime *or* evening)	**go to street**
	on street *and* protesting	**go to square**
	on street *and* know-of-protest *and* $e_i > s_i$	**go to square**
	on street *and* know-of-attack *and* $e_i \leq s_i$	**go home**
	employed *and* night	**go home**
	not employed *and* night	**go home** with probability P_{ugn}
attack		
Citizen	on street *or* on square	attacked is on with probability P_a
		all local citizens: know-of-attack is on
influence		
Facebook	any citizen know-of-protest	show-protest is on
	any citizen know-of-attack	show-attack is on
Citizen	any close influencers know-of-protest	know-of-protest is on
	any close influencers know-of-attack	know-of-attack is on
	Facebook show-protest	know-of-protest is on
	Facebook show-attack	know-of-attack is on
		$e_i = max\left(e_i, \frac{1}{n}\sum_j e_j\right)$, where j iterates over n immediate influencers
	know-of-attack *and* not at home	$e_i = e_i + 0.1$, truncated at [0,1]

(*Continued*)

Table 1. (*Continued.*)

Agent	Condition	Action
protest		
Citizen	not at home *and* $e_i > s_i$	protesting is on
		know-of-protest is on
		Facebook: show-protest is on
Special sets of actions		
go home		
Citizen		stay-home is on
		protesting is off
		move to home
go to street		
Citizen		move to street with probability $1 - \frac{TD}{100}$
go to square		
Citizen		move to square with probability $1 - \frac{TD}{100}$

Notes: If no condition is specified, the action occurs in any time period; e_i refers to the level of emotion of citizen i; s_i is the safety probability, the threshold of emotion for citizen i to turn to protest, given a particular level of emotion; μ_d and σ_d are the average level of dampening of emotion, and the variation therein, respectively; P_{ugn} is the probability that unemployed go home at night; P_a is the probability of a government attack; TD is the travel difficulty; close influencers are friends plus citizens in the same location; immediate influencers are citizens in the same location.

Another motivator related to protest behaviour is the social network of friends, who are likely to phone each other up with news or visit them in person (Finding 3; also see findings of social media studies). The construction of this static network is controlled
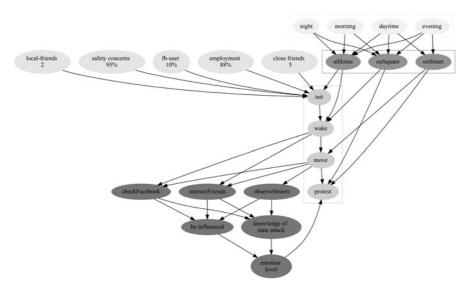

Figure 1. Basic Model Parameters and Behaviours Excluding Emotions
Note: Emotions are displayed separately – see the Online Appendix.

by two parameters called 'av-num-friends' and 'locality-friends'. Each parameter ranges from 1 to 10 and is set at a certain value in the initialization stage. In the initialization, the parameter av-num-friends was set at 5. This setting is based on Robin Dunbar, who has specified 5 as the maximum number of close friends (Mac Carron et al. 2016). For friends in the same neighbourhood, addressed by the parameter locality-friends, we lowered the initialization value to 2 – meaning that this network has the maximum tendency to be local to their own neighbourhood.

In the simulations, both friends and other citizens can influence protest behaviour by observing each other protest, which can result in a higher emotion level (Finding 3). These observations can be made in the same location or on Facebook, modelled through a separate parameter called 'fb-user%', which can be set at a value between 0 and 100 in the initialization phase. In the simulations, this parameter is set at 10. This value is based on numbers for Facebook users in Egypt, which ranged from 5.49% in December 2010 to 13.4% in May 2012 (al-Ahram 2012; Arab Social Media Report 2011).

Protest space

The space in the model consists of three locations: homes, streets and a square. Protest takes place on the square, and in order to participate, agents need to move from their homes through the streets. Individuals can be mobilized in their homes through interactions with others by phone and Facebook. These interactions may create knowledge of the protests, and of whether other citizens have been attacked. On the street and in the square individuals can furthermore be affected through face-to-face interactions.

The simulation includes a temporal dimension unfolding in four stages over the course of a day: waking, daytime, evening and night. During waking, emotional levels are modified based on the settings of the parameters 'av-wake-dampening' and 'wake-sd'. Knowledge of protest is also reset (since this knowledge represents what has happened that day). During the daytime, unemployed people may protest on the square, and during the evening, unemployed and employed individuals may protest on the square. In the night, the employed go home while the unemployed may stay on the square. The Online Appendix provides further information.

The simulations differentiate between short-term effects and long-term effects of repression. Short-term effects occur over the course of a day during which a certain repressive measure is being applied (see Figure 3). Long-term effects can occur after a repressive measure has ended. In the simulations presented repressive measures are applied for window of 30 days, to allow us to see these longer-term impacts (the Online Appendix shows visualizations). All simulations were run for a time frame of 100 days.

Repression types

Repression types (Finding 4) are modelled by four parameters. Violent attacks are modelled by a parameter called 'gov-attack-prob'. This parameter ranges between 0.0 and 0.1, which is the probability that each agent in the street or square may be 'attacked' in each simulation time click. Attacked protesters are marked as

victims, and knowledge about their attack can spread through individuals in the same location, through Facebook or through the social network.

Street blockages are modelled based on a parameter called 'travel-difficulty%', which is set at a certain value ranging between 1 and 100. The higher the value, the more movement to the street or the square is blocked. Facebook cuts are modelled by the aforementioned parameter 'fb-user%' and 'fb-on?' – the former is the normal percentage of the population online (usually 10%) and the latter is whether this has been blocked by the government or not. Curfews are modelled by a parameter called 'curfew', which can be set at various times during the day. If the parameter is set to a certain value, all streets are blocked from that time of day onwards. In the simulation, a day is divided into 10 periods, so that a value of 10 is equivalent to no curfew.

Various simulations presented below set parameters for repressive measures such that no repressive measures are in effect. In others these are turned on for a period of 30 days at different levels. The corresponding input values for simulations without the repressive measures are 0 for state violence ('gov-attack-prob') and street blockages ('travel-difficulty%'), and 10 related to curfews ('curfew') and Facebook cuts ('fb-user%').

Simulations

Emotional context and protest conditions

To investigate protest levels, we first ran the model with varying input levels of population numbers (2–2,000), while setting the parameters for repressive measures such that there is no repression. In these simulations, protest levels are dominated by the emotional characteristics – 'av-wake-dampening' and 'wake-sd'. High dampening and low variance in emotions are associated with low protest numbers, whereas low dampening and high variance in emotions are associated with high protest numbers. The Online Appendix provides visualizations.

The parameters representing emotions identify four protest conditions that offer an immediate and dynamic context for protest behaviour (see Online Appendix and Figure 2): 'high', 'sup-critical', 'critical' and 'low' conditions. Although other parameters affect the outcomes, these conditions dominate the others, thus we look at impacts within each of these conditions.

- In the 'high' condition, a maximum number of protesters are on the square throughout the simulation. This condition is related to high levels and variance in emotions. The related settings of the emotional parameters are 0.5 ('wake-sd') and 0.95 ('av-wake-dampening').
- In the 'sup-critical' condition, a medium number of protesters are on the square with a tendency of reaching the maximum protest levels. The sup-critical condition is related to setting both emotional parameters at 0.45.
- The 'critical' condition exhibits low numbers of protesters, which increase but then drop again. The critical condition is based on setting the emotional parameters at 0.4.
- In the 'low' protest condition, there are minimum numbers of protesters. The related setting of the emotional parameters is 0.3.
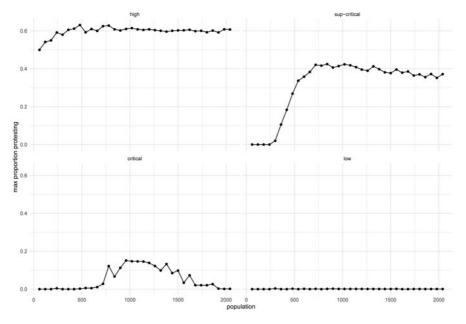
Figure 2. Maximum Protesting Population Shares in Each Condition during the Last of 100 Simulation Days

Notes: Each point represents an average over 20 independent simulation runs, given population numbers between 0 and 2,000 as input. The remaining parameters were set at the values specified above (see model description). The parameters of repressive measures were excluded from the analysis.

Comparing repression effects

The following simulations explored short- and long-term effects of repression. Short-term effects are observed during the course of a day, whereas long-term effects are observed during the 30 days of repressive measures and after. The total simulation time frame covers 100 days.

We examine the effects of each repression type separately, by varying the input values of a particular repression parameter, while setting the remaining parameters such that there is no repression of the remaining types. Each repression effect is examined in the four protest conditions identified above. The remaining are constant, as described above.

Dampening effects (short-term)

The simulations show that the effect of repression depends most upon the kind of condition that the simulation is in (the four conditions described above). Given this, repression has a short-term dampening effect, consistent with the literature highlighting that repression deters dissidents from challenging the state (e.g. Davenport 2015; Muller and Weede 1990). In the model, most repressive measures visibly reduce the average numbers of protesters in high, sup-critical and critical conditions, while pre-empting protest in low conditions. Contrary to widespread assumptions, in our model the maximum dampening effects are associated with non-violent, rather than violent repression types.
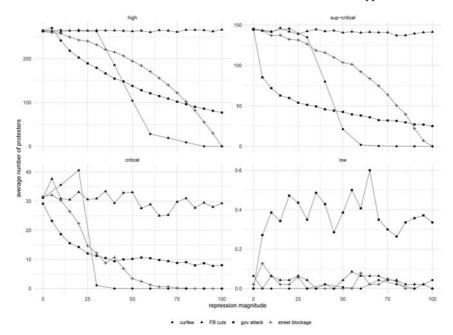
Figure 3. Repression Effects in High, Sup-critical, Critical and Low Conditions on the Average Number of Protesters during the Last of 100 Simulation Days
Notes: Each point represents an average over 20 independent simulation runs. To calculate the magnitude of repression, the curfew and governmental attack parameters were rescaled, so that their values range from 0 (lowest) to 100 (highest).[5] The parameters of street blockages and Facebook cuts did not need rescaling (see model description). The scale showing the average number of protesters is adjusted to the protest conditions (high–low).

Offline blockages of the infrastructure in the form of street blockages and curfews maximally reduce the numbers of protesters. In the high and sup-critical conditions, the maximum effect of offline blockages of the infrastructure occurs when all streets are closed, or a curfew during the vast majority of the day is imposed. In the critical condition, blockages of 60% of the roads maximally reduce protest behaviour. By contrast, state violence does not reduce the number of protesters to zero, and displays some spurring effects, discussed in the next section. Unlike street blockages and curfews, the strongest dampening effects of state violence are moreover associated with its lowest magnitudes. Facebook cuts are the only repressive measure that shows no comparable dampening effects, and this due to the fact that the same information tends to be disseminated via personal networks (Figure 3).

Spurring effects (short- and long-term)
Consistent with theories arguing that repression increases dissent (e.g. Francisco 1995, 1996; Hafez 2003), we identify spurring effects of state violence within a given protest day (Figure 4). This effect is not observable for any of the remaining repressive measures (see Online Appendix). The spurring effect of violence is most visible in the critical protest condition with maximum numbers of protesters. In this condition, the level of state violence initially reduces protest numbers, but as
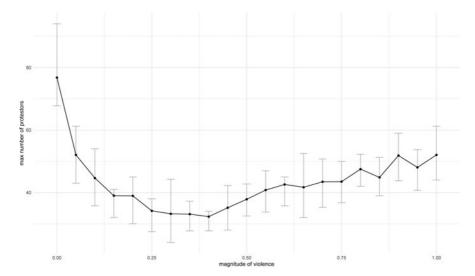
Figure 4. Effects of Continual State Violence on the Maximum Number of Protesters in the Critical Condition

Notes: Each point represents an average over 20 independent simulation runs on the last of 100 simulation days. The error bars range from the 25th to the 75th percentile.

the level of violence grows, protest numbers increase again. Accordingly, the distribution is U-shaped (Figure 4). In this model, high levels of violence do remove people from public spaces but can also increase the levels of emotion, which can result in a longer-term increase in protest.

This finding complements studies arguing that repression has immediate spurring effects, which turn into a dampening effect as repression increases and reaches a certain threshold (e.g. Bell and Murdie 2018; Lichbach 1987; Muller and Weede 1990). While confirming that the effects of repression are non-linear, our finding suggests that the magnitude of state violence might be less important than usually assumed. Rather than deterring dissent when applied beyond a certain threshold, in our model, state violence is found to have a deterring effect when applied minimally, but can have a motivating effect when applied at higher levels.

The simulations investigating long-term effects provide additional support for spurring effects. These relate to both the effects after the application of repression, and effects during its application over 30 days. The strongest model effects are associated with state violence, whereas the weakest are related to Facebook cuts (see Online Appendix).

Most long-term spurring effects are related to the critical and sup-critical protest conditions, suggesting that repression has the potential to fuel low- to mid-scale dissent (see Online Appendix). The simulations do not identify comparable spurring effects in high or low conditions where masses protest, or where very few protesters are in the streets (see Online Appendix). Consistent with threshold models of protest (Granovetter 1978; Kuran 1991; Noelle-Neumann 1974), these findings suggest that repression may not deter dissent in the long term, once large-scale uprisings are happening. Nevertheless, they also suggest that repression can have

long-term pre-emptive effects in conditions with low protest numbers, underlining that repression has both deterring and spurring elements (Rasler 1996).

Post-repression effects show maximum spurring related to violence with high, and not low, magnitudes (Online Appendix). This further supports the finding that increasing magnitudes of violence have the potential of spurring rather than deterring dissent in the medium term (cf. Figure 4). Nevertheless, effects during the application of state violence show maximum spurring under low magnitudes of violence (in critical conditions), or fail to identify spurring effects (in sup-critical conditions). In the modelled sup-critical condition, increasing magnitudes of violence have the potential of dampening dissent, while spurring is only visible after the application of violence (Online Appendix).

Conclusions

To explore the opposing effects of repression on dissent, this article presents an agent-based model developed from ethnographic interviews with dissidents. Drawing on the psychology literature on protest, the model integrates emotions as a dynamic context of dissent. The findings provide new, micro-level insights that help clarify how the dampening and spurring effects of repression might occur. Based on our ethnographic research, the model assumes that violence is the only form of repression that heightens emotions, emotions that in turn increase agents' willingness to turn out to protest. We find that repression can spur protest, while non-violent forms of repression might suppress dissent.

The analysis identifies short-term dampening effects, in which repression motivates safety-based, risk-averse reasoning among potential dissidents. This finding advances the broader repression literature on dampening effects of repression (e.g. Davenport 2015; Lichbach 1987; Moore 1998; Zhukov and Talibova 2018). Differentiating between short-term and long-term effects, it suggests that dampening may occur in the short-term aftermath of repression, rather than long afterwards. It also links short-term dampening to specific dissident reasoning processes, which have not previously been included by the literature on the state–dissident nexus. Specifically, it suggests that suppression of protest can be associated with safety concerns that discourage people from mobilizing against states that are exercising repression.

Contrary to expectations from existing theories associating high repression magnitudes with dampening (e.g. Bell and Murdie 2018; Lichbach 1987; Muller and Weede 1990), the maximum dampening effect identified by the analysis is associated with non-violent repressive measures, and not state violence. Our simulations moreover suggest that state violence might not only have weaker effects than non-violent measures in the short term, but could also spur dissent more than any other repressive measure in the long term. On the one hand, this finding contrasts with widespread assumptions that violence deters dissent by increasing the cost of dissident behaviour (e.g. Lichbach 1987) or instilling dissidents with emotions of fear (e.g. Pearlman 2016). On the other hand, this finding is consistent with new research showing that high levels of oppression and associated emotions of fear may not deter individuals from engaging in non-violent resistance, as is usually believed (Dornschneider 2021b).

The analysis furthermore identifies possible long-term spurring effects of curfews, street blockages and Facebook cuts. Although less strong than the related effects of state violence, these findings indicate a trend in which repression increases dissent in the long term. This finding adds to theories on spurring effects of violence (e.g. Francisco 1995, 1996; Hafez 2003; Toft and Zhukov 2012) by suggesting that spurring may happen primarily in the longer-term aftermath of repression. As such, it contributes to the debate on the short-term versus long-term effects of repression (cf. Rasler 1996; Rozenas et al. 2017; Zhukov and Talibova 2018) and provides new support for theories suggesting that repression has long-term spurring, rather than dampening effects (e.g. Rasler 1996).

Building on recent research findings on emotions, our analysis identifies and formalizes a social tipping process typified in the four different protest conditions studied. In this context, the spurring effects of repression are particularly noticeable under critical conditions, in which emotional levels warm up and protest emerges, as opposed to emotionally charged conditions where masses protest anyway, or emotionally 'cool' conditions with low numbers of protesters.

The article highlights the value of ABM to better understand the state–dissident nexus. Much of the existing knowledge is related to structural factors or theoretical accounts of decision-making. ABM instead focuses on individual behaviour and interactions to explore the social dynamics of state–dissident interactions. This focus adds insight into how micro-level non-violent dissent might result in various macro outcomes, providing a more nuanced understanding of its social tipping processes, and facilitating the development or more fine-grained hypotheses.

The findings emphasize the value of integrating emotions into models tracing the micro-foundations of dissent. Emotions underlie differences in the protest behaviour of individuals in the same context, as shown by ethnographic field research on the Arab Spring. Many Arabs reacted to the uprisings by worrying about their safety. In the words of a non-participant, 'This [protest] brings killing, war, and blood.' By contrast, participants felt overwhelmed by positive emotions. A Moroccan protester said he could not believe his eyes when he suddenly saw thousands marching in the streets: 'It was incredible.' Integrating these differing experiences helps to make sense of protest dynamics, which continue to puzzle social scientists and protest participants alike. In the words of the same Moroccan, 'Out of the blue, everyone showed up.'

Notes

1 See Yuen (2015) on the importance of road blockages from the dissident perspective.
2 Rather than commenting on authoritarian structures, interviewees referred to the behaviour of state actors within these structures. The Online Appendix provides more information.
3 A thorough account is Edmonds and Meyer (2017).

4 The complete code and a technical description of the simulation is available in Edmonds and Dornschneider (2019). The Online Appendix provides a detailed overview of the main features.

5 'gov–attack–prob' was multiplied by 100. 'curfew' was multiplied by 10 and deducted from 100.

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