# An agent-based model of protest diffusion and thresholds

Stephanie Dornschneider and Bruce Edmonds[1]

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This paper presents an agent-based model of protest diffusion and thresholds, developed from ethnographic interviews with dissidents in two repressive settings in the context of the Arab Spring (Egypt and Morocco; N=92). Previous qualitative analyses and related ethnographic interviews have established that dissidents in these settings are motivated by the behavior of others in their environment, combined with positive emotions of hope, courage, solidarity, and pride (Dornschneider 2019). This brings in the individual perspective to more context-based explanations of protest behavior. While a range of theories exists about the conditions under which protest is more likely, few explain the variation between individuals within the same context in terms of their protest behavior.

In this paper, we take the next step towards developing a new theory of protest behavior by investigating an agent-based model (Axtell 2000; Gilbert 2004; Epstein 2007; López-Paredes et al 2012), where the rules of behavior of the model are derived from the qualitative analyses (cf. Edmonds 2015). We apply the model to examine theories on protest diffusion and thresholds (Granovetter 1978), according to which protest decisions depend on the number of preceding protest decisions by others. Our application identifies four protest thresholds that complement the existing literature by specifying when 1) individuals begin to mobilize; 2) a critical mass shows up for protest; 3) mass protest occurs; and 4) protest declines.

Existing theories explain protest thresholds through preference falsification (Kuran 1991), according to which individuals hesitate to reveal their true preferences and join protest unless a sufficiently large number of protestors is observable, as well as the spiral of silence (Noelle-Neumann 1974), according to which individuals stay silent rather than voice their opinion to avoid social isolation. Our model adds to this literature by linking protest thresholds to emotions (Jasper 1998), which are a well-known, yet often ignored factor underlying individual protest behavior, especially in the diffusion literature. In our model, individuals are more likely to protest if emotion levels increase. Emotion levels in turn depend on knowledge of protest, interaction with protestors (online and offline), and state repression in the form of governmental violence, curfews, and state interventions on the online protest infrastructure.

Establishing the link between macro-level patterns and individual-level behavior is a perennial problem in social science (Elster 2007). This paper explores a model that links the micro-level decision making of individual potential protesters, with macro-level patterns of protest, their related emotions, and state repression. It therefore contributes to our theoretical understanding of protest diffusion and thresholds, while providing hypotheses for further investigation into our psychological and behavioral understanding of protest behavior.

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## Protest Thresholds and Emotions

Threshold models identify a social tipping process in which protest movements take off once a sufficiently large number of people participate in them (Granovetter 1978; Yin 1999; González-Bailón 2011; Enikolopov, Makarin and Petrova 2020). The underlying logic of this decision-making process has been related to preference falsification (Kuran 1991; Jiang and Yang 2016; Crabtree, Charles, Kern, and Siegel 2020) and the spiral of silence (Noelle Neumann 1974; Scheufle and Moy 2000). According to these concepts, people refrain from public protest in the absence of a sufficiently large movement because they fear governmental persecution (preference falsification) or social isolation (spiral of silence). Consequently, emotions of fear are considered key in the mobilization process.

Consistent with this understanding, much of the broader protest literature acknowledges the importance of emotions. Emotions are subjective experiences that arise in the context of certain situations and involve action tendencies (Frijda1988), which play a key role in political dissent (Goodwin, Jasper and Poletta, 2001; van Zomeren, Postmes and Spears, 2008; Pearlman 2013; Jasper 2014; Spring, Cameron and Cikara 2018; Young 2019).

The protest literature typically emphasizes the importance of emotions during the built-up and spread of nonviolent dissent, focusing on anger (e.g. Ayanian and Tausch 2016; Jasper 2014; van Zomeren, Postmes and Spears, 2008), as well as frustration (e.g. Gurr 1970; Davies 1962) and moral outrage (e.g. Spring, Cameron and Cikara 2018; Goodwin, Jasper and Poletta, 2001). At the individual level, these emotions arise from perceptions of injustice among the members of disadvantaged social groups (van Zomeren, Postmes and Spears, 2008). At the societal level, they are associated with relative deprivation in the distribution of power and wealth (Gurr 1970; Davies 1962; also see Chenoweth and Ulfelder 2017; Fearon and Laitin 2003; McAdam, Tarrow and Tilly 2001).

Contrasting with this understanding, the literature on protest thresholds suggests that fear plays a negative role during mobilization processes. Research on protest (Young 2019; Pearlman 2013), rational choice (e.g. Lichbach 1987) and social networks (e.g. Amos, Kuhlman and Ravi 2020) has provided empirical evidence in support of this assumption. Nevertheless, to our knowledge, there are no models that systematically integrate emotions to study protest thresholds to date. Given the importance of fear in threshold models, this is an especially important omission.

Our agent-based model is developed from new research on dissident reasoning (Dornschneider 2019, 2021). This research finds that repression may fuel political dissent through positive emotions (Finding 1), which strengthen and widen action-oriented thinking (Fredrickson 2003). Specifically, dissident decision-making is connected to positive emotions of solidarity with the victims of state repression, hope that nonviolent 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 spur the mobilization process, which we include in our model.

Our model also integrates the new finding (Dornschneider 2019, 2021) that individuals refrain from participating in nonviolent 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 behavior. This finding is consistent with studies showing that cognition and emotions interact with each other (Lerner and Keltner 2001; Lazarus 1982), and that emotions are more than simple reflexes disconnected from thinking (Jasper 2018).

Our model moreover integrates the finding (Dornschneider 2019) that the behavior of others is the main source of emotions (Finding 3). This finding is consistent with social contagion and threshold theories of protest and new conceptualizations of protest cycles (Chang and Lee 2021), according to which nonviolent dissent spreads based on the protest behavior 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 protestors 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.

## Agent-Based Modelling

ABM[i] is a computer simulation approach in which each actor is represented by a separate entity, called agents. Each agent has its own characteristics and behavior. When the simulation is run, the agents act in parallel – interacting with each other depending on their state, knowledge, interactions and situation in the simulation. Understanding what has happened in a simulation can be complex, but it is open to indefinite inspection and experimentation. In this paper, we focus exclusively on protest numbers and thresholds. The detailed findings complement existing studies by providing new, micro-level insight into the social-tipping processes underlying mass mobilization.[ii]

ABM has a number of crucial advantages for studies of political protest: (a) It relates the micro-level (the cognition and actions of the agents) to the macro-level outcomes, allowing this relationship to be better understood; (b) it allows modeling the agents' behavior based on any desired decision-making pattern, including heuristics as well as rational choice deliberations; (c) it permits differing rather than uniform behavior of agents in varying social, temporal and geographic contexts; and (d) it integrates a variety of kinds of evidence, such as micro-level accounts of decision-making, evidence about social networks and macro-level characterisations of outcomes.

The emerging literature applying ABM to related studies 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), as well as complex dynamics related to decentralized rebellion and interethnic civil violence (Epstein 2012). The following application contributes insight into the emotional dynamics underlying tipping points in the spreading of dissent.

While ABM can be used for many different purposes (Edmonds and al. 2019), our study explores the possible macro outcomes that result from implementing behaviors based on qualitative interview accounts, following Moss and 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 empirically validate these findings.

# 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 (Finding 1) and protest behavior of others (Finding 3). The first process refers to changing movements of the agents in the model space, that is, the patch of a street, the square, or a home (see below "protest space"). The second is a social contagion process concerning the emotions discussed above. This is a kind of threshold-contagion process, in which emotions spread across individuals, as they move across the model space.

In each location, the emotional levels of individuals go up to match that of the average in the location. If the average is below that of an individual, nothing happens.

We model background emotion dynamics by two parameters which represent the wider emotional characteristics of the population, namely “av-wake-dampening” and “wake-sd.” These parameters control the processes that affect emotions for reasons that are external to those in the model. Both “av-wake-dampening” and “wake-sd” are dynamic and vary between 0 and 1. “av-wake-dampening” is how fast emotions fade in the population on average. A value of 0 would mean all emotions of the previous day had dissipated, a value of 1 would mean that none were. “wake-sd” is the variation in the amount of emotions that are due to events not represented in this model each day on average. A value of 0 means all emotions are due to the processes in the model, higher values indicate the level of random emotional fluctuation that occur to individuals for other reasons.

During the course of a protest day, the emotional level of individuals can increase based on their knowledge of protest, which they obtain through interactions with others. Knowledge of government violence also increases the level of emotion. The higher the emotional level of a population and its variation across individuals, the higher the protest likelihood. This relationship is visualized by Figure 2.

### *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 initialisation process, and is subsequently assigned to individuals based on a random normal distribution in the simulation (with this average). The higher individuals' 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 behavior. In the following simulations, the parameter is initialized at a high value of .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 protest behavior is the social network of friends, who are likely to phone each other up with news or personally visit them (Finding 3; also see findings of social media studies). The construction of this static network is controlled by two parameters called “av-num-friends” and “locality-friends”. Each parameters ranges from 1 to 10 and is set at a certain value in the initialisation stage. In the initialization, the parameter av-num-friends was set at 5. This setting is based on Dunbar, who has specified 5 as the maximum number of close friends (Mac Carron et al., 2016). For friends in the same neighborhood, 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 neighborhood.

In the simulations, both friends and other citizens can influence protest behavior by increasing individuals' protest knowledge (Finding 3), which subsequently translates into a higher emotion level and protest behavior. Protest knowledge can also be communicated by social networks online. These are modelled through a separate parameter called “fb-user%,” which can be set at a value between 0 and 100 in the initialisation 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 (Arab Social Media Report, 2011; al-Ahram 2012).

Another motivator related to an agent's protest behavior is modelled by a parameter representing the employment level of the population, namely "employment%" (Finding 4). This parameter takes values between 0 and 100 and is set at a certain value in the initialisation 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, 2012).

### *Protest space*

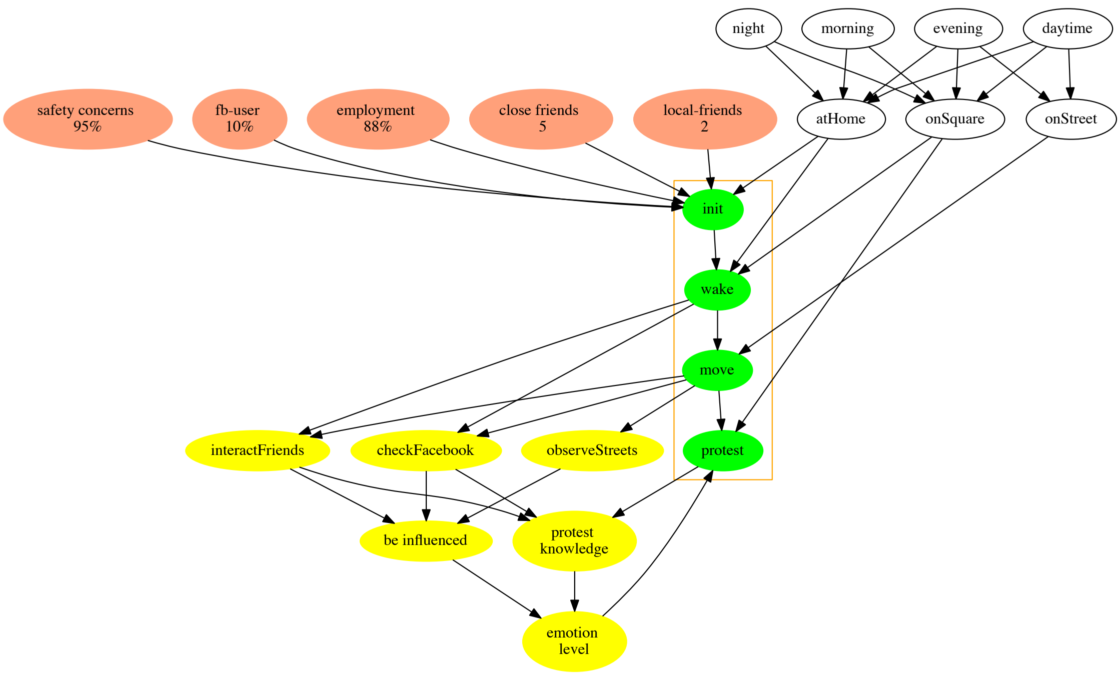
The space in the model consists of three locations: homes, streets, and a square. Protest takes place on the square, and in order to participate, agents need to move from their homes through the streets. Individuals can be mobilized in their homes through interactions with others by phone and Facebook. These interactions may create knowledge of the protests, and subsequently translate into a higher emotion level. On the street, individuals can furthermore be mobilized through face-to-face interactions, which have the same effect on their knowledge of protest.

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 may protest on the square, and during the evening, unemployed and employed may protest on the square. In the night, the employed go home while the unemployed may stay on the square.

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 5). Long-term effects occur after a certain repressive measure has ended, and over the time frame of 30 days during which a repressive measure is applied (see Figure 7). All simulations were run for a time frame of 100 days.

**Figure 1**

Figure 1. Basic model parameters and behaviors excluding emotions (displayed separately, see Figure 2)



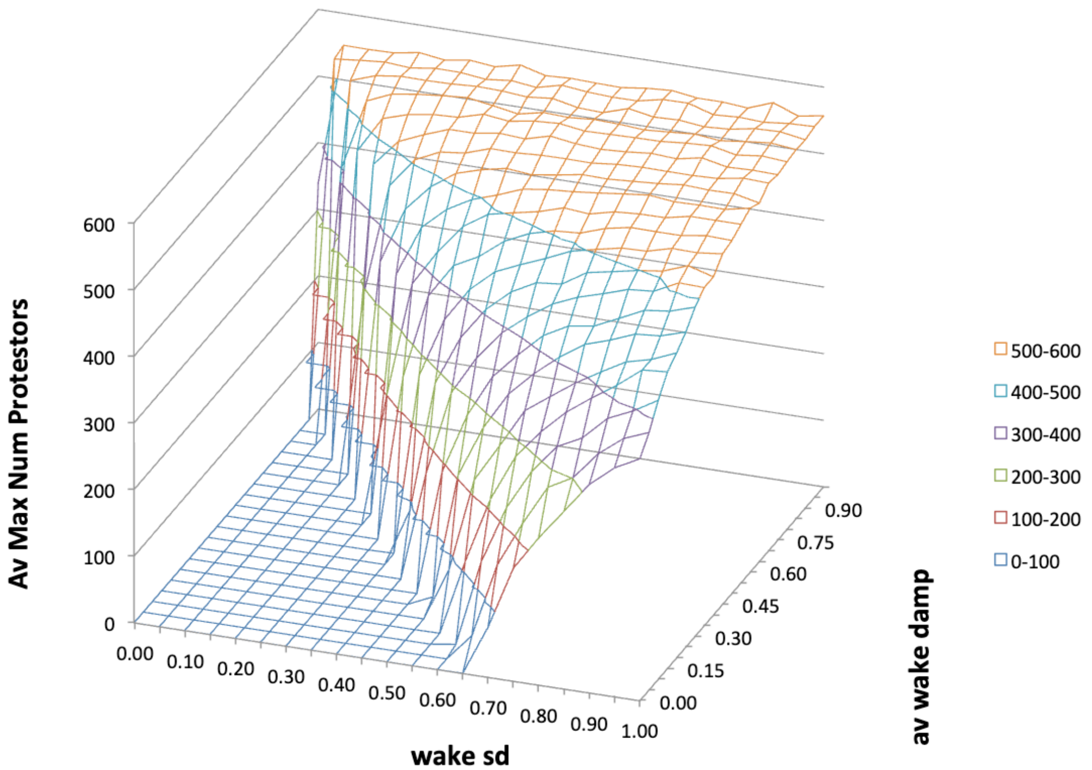
## Simulations

### *Protest conditions*

To investigate protest thresholds, we ran the model with varying input levels of population numbers (2-2000). In these simulations, protest levels are dominated by the emotional characteristics – "av-wake-dampening" and "wake-sd". Low levels and variance in emotions are associated with low protest numbers, whereas high levels and variance in emotions are associated with high protest numbers. Figure 2 visualizes this context.

**Figure 2**

Figure 2. 3D view of emotional level (av wake damp) and emotional variation (wake sd) in relation to protest behavior. The figure visualizes maximum number of protestors on the last of 100 simulation days. The parameters were set at the values specified in the Model Description. The parameters of repressive measures were set such that there is no repression.



The simulations identify four protest conditions that offer an immediate and dynamic context to study protest behavior (figures 3 and 4). These conditions speak to threshold theories of protest, because they are associated with varying numbers of protestors ranging from “low” to “high,” which disaggregate the mobilization process.

The “high” condition represents an above-threshold stage of protest, as it displays a maximum number of protestors 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 .5 and .95.

The “sup-critical” condition represents a protest stage during which a certain threshold is met, as it shows a medium number of protestors 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 .45.

By contrast, the “critical” condition represents a stage below the threshold, exhibiting low numbers of protestors. In the critical conditions, however, we see protest numbers increase towards the sup-critical stage, but then drop again. The critical condition is based on setting the emotional parameters at .4.

In the “low” protest condition, there are minimum numbers of protestors. This condition is the furthest away from a protest threshold. Unlike the critical condition, the low condition shows no increase of protest numbers towards the next protest stage. The related setting of the emotional parameters is .3.

**Figures 3 - 4**

Figure 3. Plan view of protest numbers varying with the parameters representing emotions. The figure visualizes maximum number of protestors on the last of 100 simulation day. The parameters were set at the values specified in the Model Description. The parameters of repressive measures were set to zero.

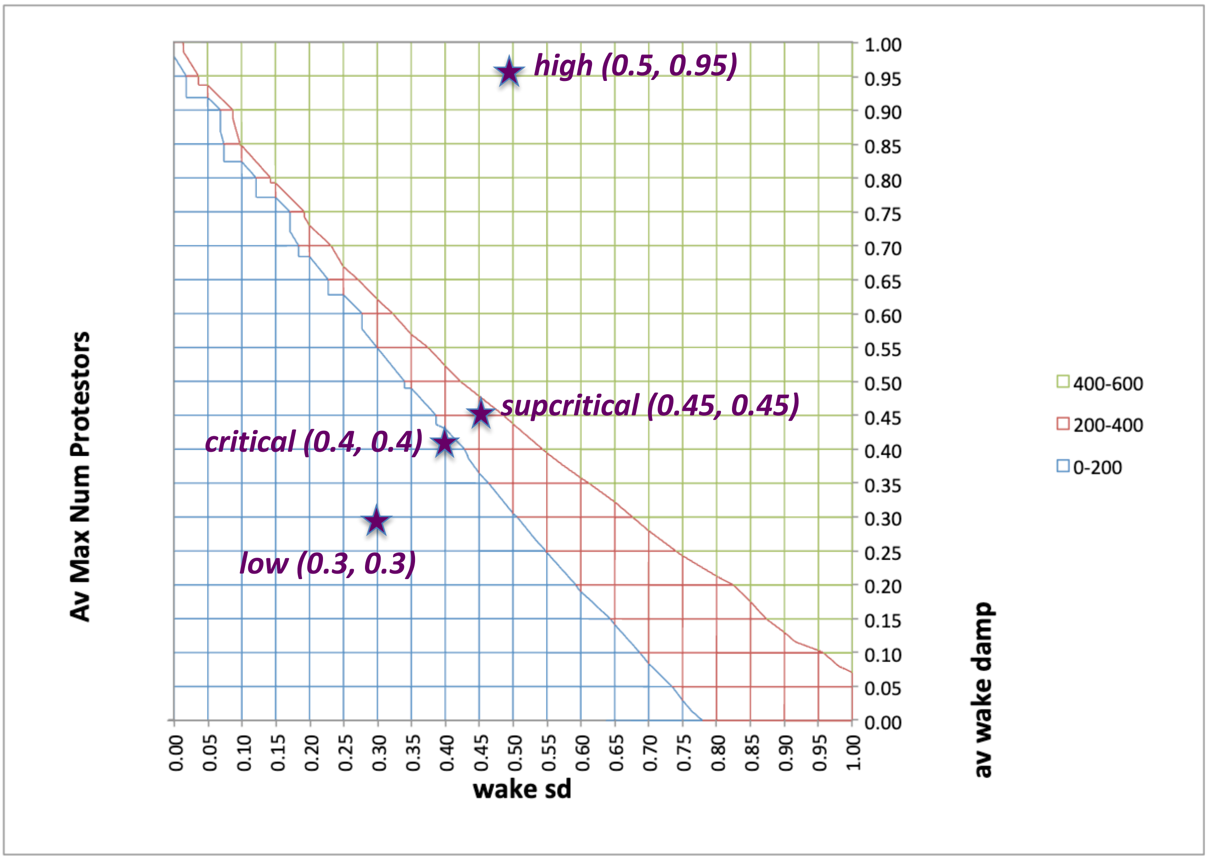
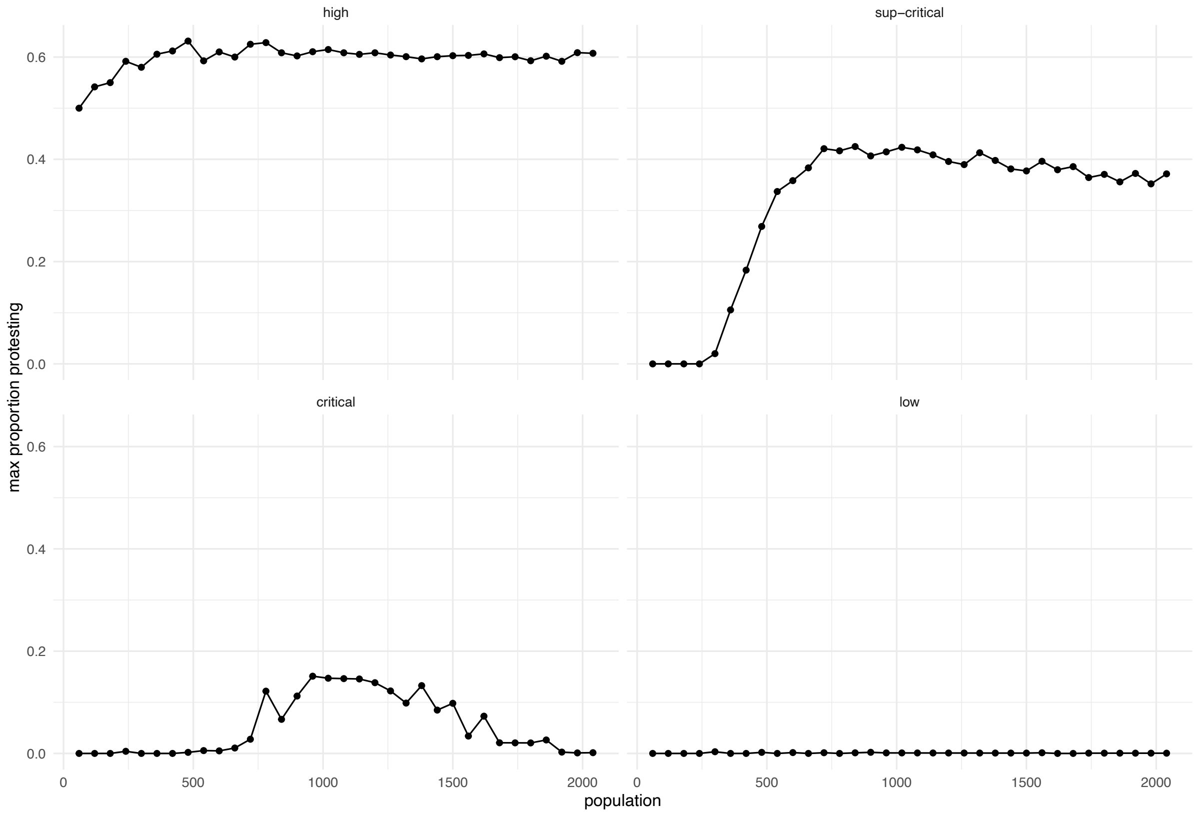


Figure 4. Maximum protesting population shares in each condition during the last of 100 simulation days. Each point represents an average over 20 independent simulation runs, given population numbers between 0-2000 as input. The remaining parameters were set at the values specified above (see Model Description). The parameters of repressive measures were excluded from the analysis.



## *Next Steps*

The four conditions add to threshold models by offering a more fine-grained account of the mobilization process underlying tipping points. In our next analyses, we will explore each of the four conditions to identify their main features, in addition to their emotional contexts. Special attention will be given to the density of the mobilization infrastructure, which is considered a key aspect of mobilization processes (e.g. Masías et al. 2021; Petrovskii et al. 2020; Schoene 2018; Lindvall 2013).

In the simulations we have run so far, density is represented by the number of people per 'house' (the unit of residence in the model).[2] Preliminary findings for the critical condition (see Figure 5) suggest that the relationship between density and protest is curvilinear (inverted-u), with a maximum protest being related to settings with average population density. These findings are consistent with existing research on strikes (Lindvall 2013), which identify an inverted-u relationship between union density and dissident behavior. According to this literature, low density prevents people from organizing themselves into a strike, a logic which might also explain why Figure 5 relates low density to low protest numbers.

Nevertheless, the preliminary findings might be surprising. In densely populated areas, more people can observe and be drawn into protests, which is why these areas might be associated with high, rather than low protest numbers. According to Lindvall (2013), high density is related to high visibility and governmental repression, which successfully deters strikes. However, our preliminary findings do not integrate state repression, and Lindvall's logic does therefore not apply.[3]

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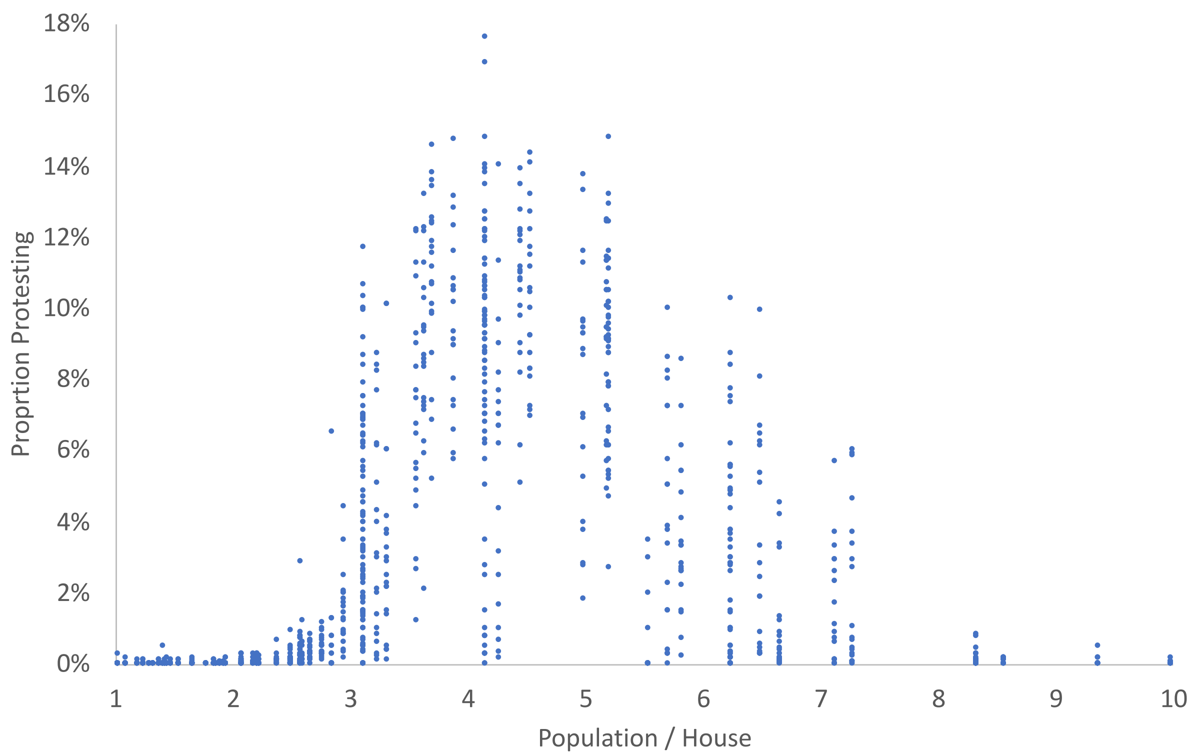
[2] The number of houses is calculated by the number of patches minus the number of roads and the square.
[3] We explore state repression and the state-dissident nexus in separate paper applying additional model parameters.

A possible alternative explanation is that the critical condition, for which our preliminary results were obtained, does not yet involve protest by a large part of the population. Therefore, protest might be more difficult to observe in densely populated areas, burdening the acquisition protest knowledge and, by extension, mobilization in early protest stages. Following this logic, we would expect the relationship between density and protest to change in the sup-critical and high protest conditions, when protest reaches a maximum level. Under such conditions, density could become a factor that spurs protest movements, and we might expect to observe a positive association between density and protest. In our next simulations, we will explore these protest dynamics, trying out alternative emotion contagion mechanisms.

Figure 5. Maximum proportion of population protesting in the critical condition based on population density. Each point represents a separate run for a different population and number of houses during the last of 100 simulation days.



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[i] An accessible introduction to ABM is Gilbert and Troitszch 2005, and a thorough account is Edmonds and Meyer 2017.
[ii] The complete code and a technical description of the simulation is available at XX. The Appendix provides a detailed overview of the main features.