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# Emergence of protests during the COVID-19 pandemic: quantitative models to explore the contributions of societal conditions

Koen van der Zwet[1,2,3✉], Ana I. Barros[2,3,4], Tom M. van Engers[2,5] & Peter M. A. Sloot[2,6,7]

The outbreak of the COVID-19 pandemic has led to an upsurge of protests. The emergence of civil resistance movements is often associated with various conditions of social systems. The analysis of social systems also shows the importance of considering the behaviour time scale and in particular slow-fast dynamics. The fine-grained datasets of the sudden and dramatic disruptive force of the pandemic can be used to better grasp the different dynamics of this social phenomenon. This paper proposes a holistic approach to explore the relationship between societal conditions and the emergence of protests in the context of the COVID-19 pandemic. First, a literature survey was performed to identify key conditions that lead to the emergence of protests. These conditions and underlying relations have been captured in a causal loop diagram to conceptualise the emergence of civil resistance as a result of intertwined dynamics. A data set is constructed for quantitative analysis. By means of statistical and computational modelling we conduct a quantitative analysis in which we compare the protest dynamics of 27 countries during the pandemic. We construct a systems dynamics model to test the explanatory value of different theoretical models on causal relationships, as our results demonstrate a strong need for other modelling approaches that better capture the complexity and underlying dynamics of protests. Our analysis suggests that while models could improve their understanding of when civil resistance might happen by incorporating variables that analyse fast changes in social systems, incorporating variables that analyse slow developments of structural conditions might further improve estimates for the severity of such outbreaks.

[1] Computational Science Lab, University of Amsterdam, Amsterdam, The Netherlands. [2] Institute for Advanced Study, University of Amsterdam, Amsterdam, The Netherlands. [3] TNO Defense, Safety and Security, The Hague, The Netherlands. [4] Police Academy of The Netherlands, Apeldoorn, The Netherlands. [5] Leibniz Institute, University of Amsterdam/TNO, Amsterdam, The Netherlands. [6] National Center for Cognitive Research, ITMO University, Saint Petersburg, Russian Federation. [7] Complexity Science Hub, Vienna, Austria. ✉email: k.vanderzwet@uva.nl

## Introduction

During the COVID-19 pandemic, several civil resistance movements have emerged against governmental institutions. According to Amenta et al. (2010) civil resistance movements are formed by 'actors and organisations seeking to alter power deficits and to effect transformations through the state by mobilising regular citizens for sustained political action'. More than 25 significant protest movements have been directly related to the COVID-19 pandemic globally in the year 2020 (Carothers & O'Donohue, 2020). An epidemic outbreak tends to disturb pre-epidemic conflicts, and create the fertile ground for the outbreak of civil resistance during and after the epidemic (Censolo & Morelli, 2020). During the outbreak of EBOLA and SARS in West-Africa and Canada, similar patterns of protests and stigmatisation were observable in West-Africa and Canada. Figure 1 illustrates the number of protests and riot events that the Armed Conflict Location & Event Data Project (ACLED) links to the COVID-19 pandemic. Although the COVID-19 pandemic has a severe and disruptive effect on the society, it also provides a unique window to study the emergence of civil resistance movements.

The COVID-19 pandemic has a large impact on societies. The disease yields uncertainty in the health care system, and the unprecedented containment measures cause social and economical disruptions. The uncertainty about the effects of a pandemic spreads fear amongst people (Madhav et al., 2017). The containment measures impose large-scale behavioural changes, and place a psychological burden on individuals (Van Bavel et al., 2020). On the individual level, these burdens are driving conditions for the development of individual emotions of stress, uncertainty, anxiety, and anger (Taylor, 2019). Moreover, containment measures can be perceived as harmful rather than helpful. In general, these changes drastically affect the ability to satisfy individual physical and emotional needs, for which the society may take emergency measures to preserve the constancy of cultural and life-supporting functions (Wallace, 1956). As the interactions between individuals ensure that individual emotions and perceptions can be easily spread and adopted, or refuted collectively, which leads to the emergence and amplification of tensions at the societal level.

This paper contributes to the development of modelling the political stability of societies, and to the study of the impact of disruptive events. First, we conduct a literature review to identify relevant conditions and their relationships. A causal loop diagram is constructed to summarise these findings and provide a conceptual understanding that brings together the different perspectives. Based on these conditions, a data set is constructed to enable quantitative analysis. We evaluate different quantitative and computation modelling approaches, which enable the analysis of societal dynamics, government interventions, and the emergence of civil resistance movements at various time scales. Most importantly, we evaluate the added value and limitations of statistical and simulation methods for understanding civil resistance movements using currently available datasets and provide future directions.

Our analysis combines a qualitative literature-based approach with statistical and computational analysis methods. This approach provides a framework to assess the contribution of disruptive dynamics on the emergence of civil resistance. We find support for a variety of existing explanations for the upsurge of protests during the COVID-19 pandemic. As various socio-economic conditions and political dynamics change at different time scales, the society is requested to adapt differently. Therefore, some dynamics might predict 'when' the onset of civil resistance will take place, while others might explain 'how'.

**Theoretical framework**. Participants of resistance movements collectively campaign for domestic regime change, secession or self-determination, or against foreign occupation (Amenta et al., 2010). Grievances, political opportunity, and mobilisation capacity are different concepts for understanding the emergence of civil resistance movements (Saxton, 2005). Grievance approaches focus on underlying conditions that motivate people to engage in civil resistance movements. According to Fearon & Laitin (2003), the ability to avert the development of grievances is often related to the capability of a government to implement adaptation measures to recover from adverse situations. Moreover, the absence of this capacity opens political opportunity for civil resistance, as a weakened government is less able to suppress mobilisation. The grievance approach is inherently related to the political opportunity approach as changes in political structure and context-specific issues create opportunities for the emergence of civil resistance (Meyer & Minkoff, 2004). For example, the transition of power can yield the perception of a weak government and instability. The mobilisation phase of resistance is argued to be a decisive factor for emergent rebellions (Goldstone, 1991). Effective rebellion depends on the number of attendees, financial support, and mobilisation of other resources, which require specific organisational skills and capacity. While some of these conditions are eminently context dependent and fluid, others, such as demographic and economic situation, are rather structural and beyond the control of activists (Chenoweth & Ulfelder, 2017).

The occurrence of various deprived societal conditions, such as poverty, state-led discrimination or a lack of civil liberties

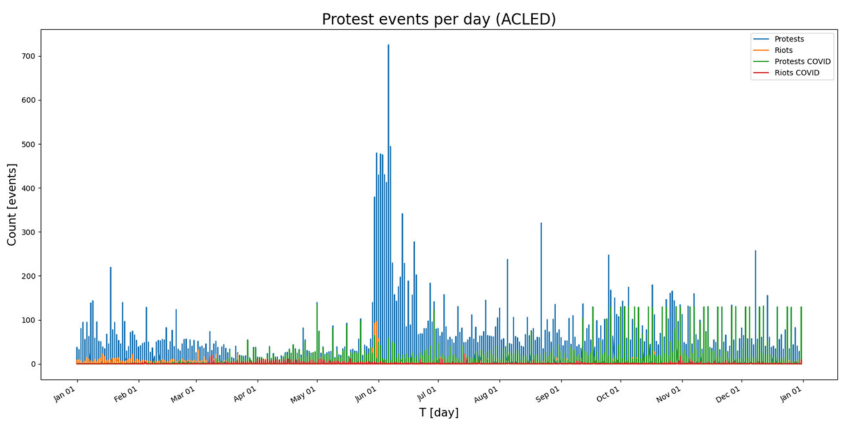


**Fig. 1 The daily number of protest and riot events in the world during the year 2020.** The data only includes countries covered by ACLED.

correlate with the onset of non-violent uprisings (Chenoweth & Ulfelder, 2017; Goldstone et al., 2010; Hegre et al., 2019). The adaptation capacity of a society is the capability to cope with societal stress and tension (Gallo, 2013). A society may become unstable and prone to conflict once the development of tension overshoot or outpace the adaptation capacity of the society. These conditions provide means for skilful activists to mobilise people to join civil resistance movements and spark the onset of protests, strikes, or other forms of civil resistance.

According to Chenoweth & Ulfelder (2017) data models that analyse the contribution of structural conditions to the emergence of civil resistance have been unable to account for agency-oriented dynamics. Furthermore, the effects of societal conditions are generalised for different civil resistance movements. These generalisations have limited the predictive power of current models. Different types of disruptive events, such as the outbreak of an economic crisis or an epidemic disease, may impact on societal stability differently. Understanding how these disruptions effect the society might yield better quantitative models.

Another limitation of most data models is that they operate on the assumption that conditions change with somewhat similar pace, as they are limited to a cross-national comparison on an annual or monthly basis. However, the structural conditions affecting human attitudes and behaviours operate on different time scales (Turchin et al., 2017). The most important aspect of analysing social systems is the understanding that these systems have multiple time scales and are high-dimensional (Hastings et al., 2018). Demographic changes occur the slowest, political elites and economic stability vary at an intermediate pace, and individual emotions change very rapidly. Since the time scales on which these representations change differ, their impact on the adaptation capacity of the society might also differ. This can be hypothesised from the theory of downward causation. While 'collective-level' dynamics -such as economic stability- result from 'individual-level' interactions, individuals can use these 'coarse-grained' representations to make strategic decisions (Flack, 2012). For example, skilled leaders of civil resistance movements could observe an increase of unemployment during the COVID-19 pandemic, and exploit this dynamic to recruit unemployed civilians.

These different conceptual approaches to explain the emergence of civil resistance provide a categorisation of conditions. In the next section, we extract various underlying conditions along each of these categories. We will describe their characteristics, such as the time scale on which they change, their stability, and describe their relationships with one another. Specifically, we will focus on the context of the COVID-19 outbreak in order to compare societal conditions in different countries.

## Methods

In the following sections we introduce a holistic analysis approach to the emergence of civil resistance during the COVID-19 pandemic. First, we discuss the theoretical basis of our approach and develop a casual loop diagram to capture these findings and conceptually model the emergence of civil resistance at a societal level. Using this conceptual model, several hypotheses on the impact of societal conditions to the emergence of protests are tested. We construct a data set of proxy variables, and develop a statistical understanding of the conditions related to the emergence of protests. These results demonstrate a strong need for other modelling approaches that better capture the complexity and underlying dynamics. Therefore, we construct a systems dynamics model to test the explanatory value of different theoretical models on causal relationships.

**Causal loop diagram**. In this section we construct a causal loop diagram (CLD) along the three categories of grievances, political opportunity, and mobilisation to provide an understanding of the underlying relations between the identified societal conditions. Additionally, we identify a set of disruptive effects upon the society from the spread of a pandemic disease and related governmental interventions. As a starting point of our analysis, we focus on dynamics during the outbreak of other diseases. Along this structure, we identify general and COVID-19-specific related psychological, societal, political, economic, and health care factors. Subsequently, we lay out expectations from this literature on how these features impact each other, and effect the emergence of civil resistance. Using these insights, we develop an integrated mapping of possible causal relationships between the identified factors to structure possible pathways of civil resistance. The resulting diagram shows the identified relationships of this system, see Fig. 2.

The resulting model brings together the different perspectives and underlying relations between the identified effects of societal conditions and dynamics of civil resistance. The spread of the epidemic disease challenges the stability of the society, as it increases the development of grievances, lowers the government legitimacy in specific population segments, and creates fear and uncertainty. An explanation of the causal links and reinforcing- and balancing loops identified is provided in the following sections.

*Grievances*. On a macro-empirical level, it is generally assumed that collective action results from discontent and relative deprivation related to objective conditions (Gurr, 1993). Social structures may deprive people from meeting their basic needs, which exposes them to structural violence (Farmer, 2009). Deprived living conditions or unequal distribution of political power is the central motivation for people to engage in civil resistance. Various underlying dynamics and conditions are related to these social structures. In some examples, factionalised elites can lead to state-led discrimination or repression of ethnic groups (Cederman et al., 2010). Furthermore, economic instability may cause unemployment, which can be related to the emergence of protests motivated by increasing food prices (Hendrix et al., 2009).

The COVID-19 pandemic directly worsened global safety conditions, as infections pressured health care capacity and caused severe increase of morbidity (CL1). Poverty is the most important risk factor for societal instability during the outbreak of an epidemic disease (Kapiriri & Ross, 2020). For example, the Ebola outbreak in Liberia was exacerbated by a lack of physical infrastructure, proper sanitation, and health facilities. Poverty prevents access to food, education and health care, which result in a high level of infant mortality and a low life expectancy, thus increasing existing grievances (CL2).

The macro-economic impact of pandemics are severe as it lowers the demand rates (Jonung & Roeger, 2006). Containment measures may lower the labour productivity and cause supply chain disruptions (Bell & Lewis, 2005). These fiscal shocks cause unemployment, and diminished tax revenues (CL3 & CL4) (Madhav et al., 2017). The necessity to invest in health care related measures claims financial resources (CL5) (Bell & Lewis, 2005).

Pandemics are marked by many psychological stressors. The widespread uncertainty, confusion, and sense of urgency creates a societal tension (CL7) as individuals deal with a psychological burden, triggered by anxiety, anger, and distress (CL6) (Taylor, 2019). The societal effects of these burdens can be immense. Owing to uncertainty, people are more vulnerable to fake news and conspiracy theories, which reinforces the uncertainty (R1) (Van Bavel et al., 2020). Groups can be stigmatised and blamed

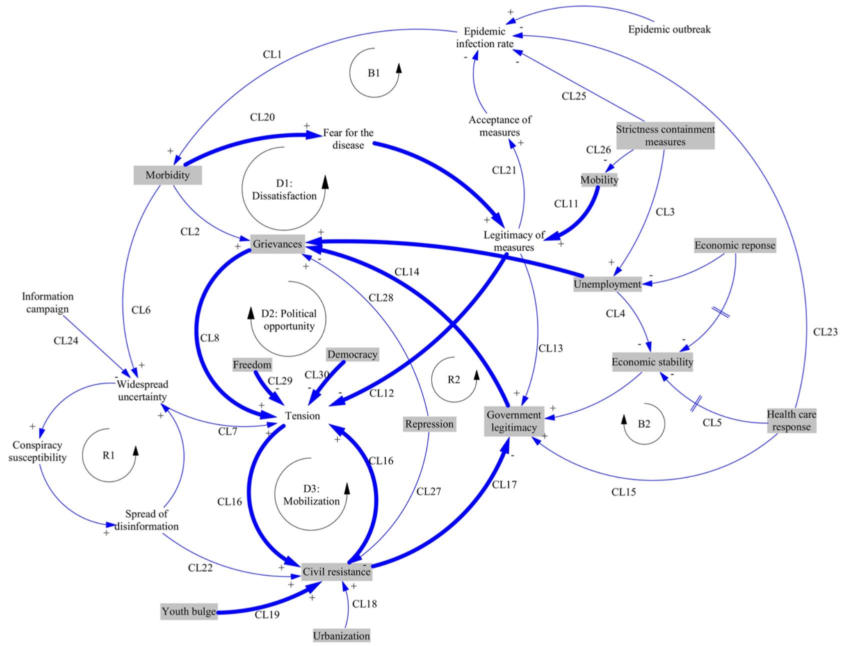


**Fig. 2 Causal loop diagram (CLD) of the pathways of civil resistance.** Variables connected with arrows indicate causal links extracted from literature. The highlighted variables are included in the data set. The thick causal links are included in the system dynamics model.

for the disease and its consequences (Kapiriri & Ross, 2020; Madhav et al., 2017). This can lead to social tension (CL8), and eventually the emergence of civil resistance (Person et al., 2004).

*Opportunity*. Civil resistance does not happen in a vacuum, rather the goals, strategies, and tactics of activists aim to capitalise upon specific opportunities provided to them (Meyer & Minkoff, 2004). Political opportunity theory aims to understand the structure, and political context, which facilitates civil resistance. Specific developments can favour the expected effect of protests or diminish the expected costs, which opens a window of opportunity for civil resistance (Engels, 2018). For example, a political transition can create an opportunity to push for reforming laws by the new incumbent (Goldstone et al., 2010). In contrary, governments that are able to provide freedom (CL29) and political rights (CL30) are less likely to be confronted with an outbreak of civil resistance (Chenoweth & Ulfelder, 2017).

During a pandemic, governments are forced to take many unpopular measures to contain the spread of the disease (e.g. quarantine and curfews) (CL11). The uncertainty about the effectiveness of different containment strategies lowers the legitimacy of such measures (Taylor, 2019). Especially states with limited state capacity risk to lose grip on governing, as they are unable to trace the effects and spread of the disease (Bell & Lewis, 2005). These issues can be politicised and open political opportunities to challenge government legitimacy (CL12 & CL13). Incompetence to deal with the effects of the pandemic perceived by the public can hurt the government legitimacy (CL15) (Madhav et al., 2017). Inadequate or conflicting information provision from government institutions can cause long-term effects of confusion and anger (R2) (Brooks et al., 2020). However, contrary to these theories, strict public-health measures imposed in the Netherlands during the severe phase of the COVID-19 pandemic actually increased the trust in the government (CL15) (Groeniger et al., 2021).

*Mobilisation*. The ability of civil resistance to gain political influence (CL17) is determined by the of number of participants (Amenta et al., 2010). Escalation from dissatisfaction to collective actions requires organisation and mobilisation (CL16) (Schroeter et al., 2014). On a state-level, the mobilisation process (Van Stekelenburg & Klandermans, 2013) can be facilitated by geographical conditions such as urbanisation (CL18) or regional contagion of civil resistance movements (Chenoweth & Ulfelder, 2017), or demographic conditions such as the 'youth bulge' in which a population consists of a higher proportion of youth (CL19) (Goldstone et al., 2010). For example, although the rate of unemployment in Egypt changed little between 1990 and 2010, in 2010 half of all Egypt's unemployed belonged to the 20-24 age cohort (Turchin et al., 2017). This group of about one million unemployed youths became the main striking force of the revolution.

The societal dynamics during a pandemic may increase cohesion and foster a politicised collective identity, which potentially effects behavioural contagion and mobilisation in several ways (Huremović, 2019). The direct and indirect effects of an epidemic disease causes the spread of fear (CL20) (Espinola et al., 2016). People tend to minimise their social interactions, which potentially slows down the mobilisation process (CL21) (Espinola et al., 2016). Next, fear tends to increase the widespread uncertainty in a society (Taylor, 2019). Owing to widespread uncertainty, more people are susceptible to conspiracy theories (Taylor, 2019). This eases the spread of misinformation or purposefully initiated spread of disinformation, which can attract people to specific movements under false assumptions (CL22). During a pandemic, adequate science communication should evaluate various interventions and treatments to reduce conspiracy theories, fake news, and misinformation (Van Bavel et al., 2020)

*Interventions*. Measures by the government aim to directly address the spread of the epidemic disease, or mitigate the other negative effects upon the society (Greer et al., 2020). Health care related measures -such as investments in vaccine development, testing and contact tracing, aim to contain the spread of the epidemic disease (CL23) (Hale et al., 2020). In order to limit the infection rate, governments are forced to implement closure and containment measures to minimise physical contact within the society (CL25) (Deb et al., 2020). These restrictions have an immediate effect upon the economy, as travel and recreational activities are limited, and people are forced to work from home (CL26). In the long-term, containment measures can cause severe traumatic psychological effects (Taylor, 2019). Implementation of fiscal, monetary, and financial policy measures governments aim to mitigate the burden upon the economic stability, state capacity and inequality (Elgin et al., 2020). A specific aspect of health care related response is the public information campaign towards citizens, which is aimed at lowering the widespread uncertainty (CL24) (Van Bavel et al., 2020). Lastly, repression can de-escalate protests in the short-term as the perceived individual price for participation increases (CL27) (Larsen, 2020). However, as repression can also escalate disorganised protests into violence (Larsen, 2020), which may increase the level of grievance (CL28), the long-term impact of repression can be quite unpredictable (Chenoweth & Ulfelder, 2017).

*Hypotheses*. The literature points to various pathways of civil resistance movements. The effects of driving factors are fundamentally differentiated by their time scale variability. For example, increasing infection rates and accompanying strict containment measures may cause a sudden tension in a society (Taylor, 2019). The socioeconomic effects of pandemic perturb the stability of the society as people require time to adapt to new living conditions. Therefore, the mobilisation of protests can be related to fast changes in the environment.

- H1: The outbreak of protests is related to changes in fast variables.

More specifically within the context of the COVID-19 pandemic, the acceptability of containment measures can be linked to the outbreak of protests. For this purpose, the short-term legitimacy of measures can be calculated as a combined factor of excess deaths and the strictness of containment measures (Guglielmi et al., 2020).

- H2: Acceptability of measures is related to the outbreak of protests.

Whereas fast changes might impose a demanding effort from the adaptation capacity of societies, structural and slow conditions might be the underlying conditions for the outbreak of civil resistance. In fact, fast changes might potentially function as the straw that broke the camel's back (Berestycki et al., 2015). Countries with worse structural living conditions might contain more people receptive to civil resistance movements. Thus, we can hypothesise these countries are more likely to experience protests phases with a higher intensity (Goldstone et al., 2010). As these grievances change relatively slowly compared to the sudden changes in the social system environment, it can be expected that slow variables are better estimators of the intensity of protests.

- H3: Slow variables influence the intensity of the peak of protests

**Datasets**. In this section we describe the data that we use throughout our quantitative and computational analysis, and enable cross-national comparison. We construct a variety of variables capturing the factors highlighted by the CLD. We link these to data proxies, see Table 1

We queried four different types of information sources. First, we use data from intergovernmental institutions to monitor economic and demographic conditions. Unemployment and gross domestic product (GDP) capture the economic dynamics. These proxies are taken from the Organisation for Economic Co-operation and Development (OECD). Urbanisation and demographic dynamics are drawn from World Bank and United Nations (UN) respectively. Second, we collect data on global living standards from non-governmental organisations (NGOs). We use the data from the Armed Conflict Location & Event Data Project (ACLED) to measure the daily number of protests events, riots, and state violence against citizens. The event data is disaggregated by type, location, and actors involved (Raleigh

**Table 1 Factors and proxies. Time scale is an indication of the velocity of change by the proxy. The temporal resolution is the actual scale on which the proxy is measured. Data refers to the data source of the proxy.**

| Factor | Proxy | Category | Pathway | Time scale | Temporal resolution | Intervention | Data |
|---|---|---|---|---|---|---|---|
| Morbidity due to the disease | Excess mortality | Health care | Grievances | Intermediate | Weekly | No | The Economist |
| Unemployment | Unemployment | Economic | Grievances | Intermediate | Monthly | No | OECD |
| Group grievance | Group grievance | Social | Grievances | Slow | Yearly | No | FSI |
| Democracy | Political rights | Political | Opportunity | Slow | Yearly | No | FH |
| Freedom | Civil liberties | Political | Opportunity | Slow | Yearly | No | FH |
| Economic stability | GDP | Economic | Opportunity | Intermediate | Quarterly | No | OECD |
| Mobility | Mobility data | Social | Opportunity | Fast | Daily | No | Google |
| Government legitimacy | State Legitimacy | Political | Opportunity | Slow | Yearly | No | FSI |
| Closures and containment | Containment measures | Social | Opportunity | Fast | Daily | Yes | OxCGRT |
| Economic stimulus measures | Economic support measures | Economic | Opportunity | Fast | Daily | Yes | OxCGRT |
| Health care response | Health care support response | Health care | Opportunity | Fast | Daily | Yes | OxCGRT |
| Stringency government response | Stringency index | Political | Opportunity | Fast | Daily | Yes | OxCGRT |
| Civil resistance | Protests & Riots | Social | Mobilisation | Fast | Daily | No | ACLED |
| Youth bulge | Population between 15 and 24, % | Social | Mobilisation | Slow | Yearly | No | UN |
| Urbanisation | Urban population living in cities, % | Social | Mobilisation | Slow | Yearly | No | World Bank |
| Repression | Violence against citizens | Political | Mobilisation | Fast | Daily | Yes | ACLED |


**Fig. 3 Comparing fast changing variables over time.** Values are standardised between 0 and 1.

et al., 2010). Since the outbreak of COVID-19, ACLED has included a specific feature that indicates whether an event is linked to the COVID-19 pandemic. Freedom House (FH) provides an annual report in which analysts rate the degree of political rights and civil liberties in countries and specific territories (Repucci, 2020). Higher values for these indexes indicate that people experience more freedom, thus score better in terms of human rights. The Fund For Peace measures the stability of countries in the opposite direction. The annual Fragile State Index provides various indicators (Uneven Economic Development, Group Grievances, Factionalised Elites, and State Legitimacy) for state capacity, legitimacy, and structural violence (Messner de Latour, 2020). Third, several proxies are drawn from research institutions. The Blavatnik School of Government systematically collects information on government policy responses to the outbreak of COVID-19. Their the Oxford COVID-19 Government Response Tracker (OxCGRT) includes 19 indicators with a daily temporal scale (Hale et al., 2020). They combine these indicators to construct four indexes, which monitor the stringency of measures in general, the rigorousness of containment efforts specifically, and the extent of health care and economic support measures to cope with COVID-19. Lastly, we use data from commercial parties. While the Johns Hopkins university provides data for tracking the evolution of the pandemic including positive infections, numerous issues remain with the official tallies (Weinberger et al., 2020). Therefore, we estimate the impact of the pandemic by the number of excess deaths, which is weekly reported by by The Economist. Furthermore, we use the Community Mobility Reports by Google to analyse the change op behaviour during the COVID-19 pandemic. This data set reports daily trends in mobility relative to the baseline, which they specify for different types movements. We include the change of residential, retail, and workplace related movement.

We could match the data proxies for 27 countries[1]. The constructed data set can be described as an unbalanced panel data set that consists of 7545 days distributed over 27 countries. The number of protests and mobility change seem to oscillate in weekly cycles, which points to a dependency to specific weekdays. However, this can partly be attributed to data collection and event reporting processes. Therefore, the daily variables are transformed to a rolling average of seven days to smoothen the effect of weekdays. Figure 3 shows standardised values for the daily number of COVID-19 related protests, the containment measures, the change in movement related to work, and the number of excess deaths. Most interestingly, we observe periods of COVID-19 protests that are characterised by a fast rise and decay of intensity, while keeping a relatively constant level of activity between these periods. Human behaviour often displays a bursty non-Poisson character, in which periods of intense activity are followed by long periods of no or reduced activity (Barabasi, 2005).

**Statistical methods**. We estimated regression models to assess the contribution of the proposed conditions on the likelihood of civil resistance. The models regress to an indicator for the daily number protest events. This count data indicator demonstrates an overdispersion and an excessive number of zeros (see S1 & S2). This indicates that during most of the days, countries do not experience protests, most likely due to an absence of social tension related to COVID-19 stress factors. Ordinary regression models for count data using a Poisson, of negative binomial (NBM) distribution would typically not fit on this data. Therefore, we apply a zero-inflated negative binomial (ZINB) regression model (Hilbe, 2011). With this model, we assume two separate processes determine the number of protests on a particular day. This can be substantiated by the theory that protests only occur when social tension motivates people to engage in civil resistance activities.

We construct both ZINB and NBM models. Slow variables are constant on a national level, as our analysis is limited to 2020. Therefore, we can only differentiate slow variables through cross-national comparison using a NBM distribution. While this limits our ability to account for longitudinal effects of slow variables, a comparison between nations allows analysis of differences in the severity and timing of the pandemic, and various containment and other governmental strategies aimed at mitigating the effects of the pandemic. The ZINB model estimates the correlations of variables along two steps. First, a logit model is estimated to identify significant factors influencing the overdispersion. Second, a negative binomial regression model (NBM) is estimated to predict the daily number of protests. The maximum likelihood estimation (MLE) method is used for optimisation (Cameron & Trivedi, 2013). The Akaike's information criteria (AIC) and log-likelihood are selected as estimators for assessing the performance of the models and model selection (Hilbe, 2011). Omitted variables are left from the models after estimating correlations using the variance inflation factor to check for multicollinearity.

**Statistical results**. The regression coefficients and AIC scores are summarised and explained in the Supplementary Information (S3-5). We begin with our findings for the fast variables. We constructed four ZINB models including grievances, opportunity, and mobilisation related variables, and an optimised model including a combination of variables. We see that the optimised model provides the best fit. We notice that low values for containment measures are associated with an absence of COVID-19 protests. This seems understandably given that people lack an urgency to protest in phases without COVID-19 related troubles. Additionally, we find evidence that unemployment can be associated with a higher likelihood of protests, while the proposed economic support measures have worked in the opposite direction. We find less evidence for the effect of repression, which actually agrees with literature that describes the nonlinear effect of repression (Chenoweth & Ulfelder, 2017).

Next, we turn to the impact of fast variables for the outbreak of protests. We compare the optimised ZINB model with an ordinary NBM model. We see that the AIC values suggest that the ZINB distribution estimates a better model. This confirms that separate processes are involved in triggering and reinforcing protests events. This aligns also with our expectation that the outbreak of protests can be related to fast variables (hypothesis 1). Finally, we compare the predictive value of slow variables. Similar to the first four models, we compare models including grievances, opportunity, and mobilisation variables, and we construct an optimised model through simulations. We construct regular NBM models as the temporal resolution of the slow variables does not allow application of ZINB distribution. We observe that the optimised NBM provides a better fit than the optimised ZINB model including fast variables. This supports hypothesis 3, as the slow variables are better estimators of the intensity of protests.

In general, our estimates suggest that countries with a high level of grievances and low levels of political rights are more likely to experience severe waves of protests. We should note that contrary to the literature, we found that countries with higher youth bulge are less likely to experience protests. Potentially, this could have been effected by the specific characteristics of the pandemic, which actually hurts old people rather than young people. Most interestingly, the results confirm that phases without protests are most likely characterised by an absence of specific social dynamics. This could be linked to the development of social tension (Berestycki et al., 2015), which can result from governmental policies, societal dynamics, and effects of the pandemic.

Overall, the log-likelihood of our models suggest that the statistical models provide modest predictive value. Our data and statistical models are unable to capture all complexity to enable forecasting conflict, similar to other studies (Cederman & Weidmann, 2017). Most likely due to latent processes, such as the development of tension, unobserved by current data or caused by nonlinear effects. Other modelling methods are required to take the inherent complexity and temporal dynamics into account.

**Computational modelling methods**. In this section, we explore the systems temporal behaviour by converting the CLD to a system dynamics model (SDM). SDMs can aid in understanding and simulating a system's emergent behaviour as they focus on feedback loops and nonlinear behaviour of variables in social systems (Sterman, 2001). Therefore, SDMs are characterised as top-down information feedback methods, which do not specify local interactions. SDMs grasp assumptions about causal relationships between model variables through expressions of dynamic behaviour with difference or differential equations. With this computational approach, we can test whether existing theoretical models for the emergence of protests provide a realistic explanation for the emergence of protest during the COVID-19 pandemic. Using our CLD and statistical analysis, we can model latent processes that yield protests as a function of significant factors identified with our statistical analysis.

Our model builds on the theoretical model of Gallo (2013), which describes internal pressure as the central factor for the emergence of domestic civil resistance. The dynamics of our model are based on two theoretical models for explaining the emergence of protests. First, we implement a model for societal tension, a factor for the level of animosity that a population has toward the government or authority, inspired by the model of Berestycki et al. (2015). Second, we model the dynamic of mobilisation, inspired by Morozov et al. (2019).

The variables the SDM (see Table 2) and their relationships (see Fig. 4) in are formulated based on the CLD. In the next section we express a set of equations to quantify these variables as stock and flows. We use the constructed data set (see Table 1 & Supplementary Information), and optimising parameters to fit the behaviour of model to the data. After explaining the model, we explore the optimisation results and behaviour of the model. The modelling steps are documented according to the Preferred Model Reporting Requirement (Rahmandad & Sterman, 2012).

*Model equations*. Tension ($T$) is the central factor in the SDM. We model tension using Eq. (1), inspired by (Berestycki et al., 2015). The function of tension is a sigmoid, which is triggered by a level of legitimacy of measures (LM) below 1 and above the tension threshold (TT) constant.

$$T_t = \frac{1}{1 + e^{-(TV+P)((1-LM_t)-TT)}} \tag{1}$$

$$LM_t = \min\left(\max\left(1 + MR_t + \frac{MBW_t + MBR_t}{2}, 0\right), 1\right) \tag{2}$$

The tension velocity (TV) parameter controls the slope of the transition from a relaxed state to a tensed state. Furthermore the number of protests ($P$) amplifies this transition process. Given the nature of the function, the level of tension fluctuating between 0 (minimum) and 1 (maximum). The legitimacy of measures (LM) is based on a simplified trade-off between mobility (MBW & MBR) and mortality (MR), which implies that mortality loosens the reduction of legitimacy caused by restrictions on mobility, see Eq. (2). The level of legitimacy is bounded between 0 and 1 (no and full legitimacy).

$$CC_{t+1} = CC_t - CU_t + CR_t \tag{3}$$

$$CU_{t+1} = CC_t \times T_t \times PV \times \frac{U + LG}{2} \tag{4}$$

$$CP_{t+1} = CP_t + CU_t - CR_t \tag{5}$$

$$CR_{t+1} = CP_t \times PV \times \frac{SPR + SF}{2} \tag{6}$$

$$CM_{t+1} = \min\left(TM \times \frac{Y \times CA_t}{(MT \times (CP_t + CA_t))^2 + (CA_t)^2} \times CA_t, (CP_t - CA_t)\right) \tag{7}$$

$$CA_{t+1} = \max(CA_t - CM_t + CD_t, 1) \tag{8}$$

**Table 2 Description of variables implemented in the SDM.**

| Dynamic | Variable | Abbreviation | Dimension | Range | Type |
|---|---|---|---|---|---|
| Pressure | Citizens | C | Persons | # | Exogenous (Data) |
| | Calm citizens | CC | Persons | (0, C) | Stock |
| | Potential activists | CP | Persons | (0, C) | Stock |
| | Social unrest | CU | Persons/day | (0, C) | Flow |
| | Unemployment | U | Persons/Persons | (0, 1) | Exogenous (Data) |
| | Government legitimacy | LG | Persons/Persons | (0, 1) | Exogenous (Data) |
| | Social adaptation | CR | Persons/day | (0, C) | Flow |
| | Freedom | SF | Persons/Persons | (0, 1) | Exogenous (Data) |
| | Political Rights | SPR | Persons/Persons | (0, 1) | Exogenous (Data) |
| | Pressure velocity | PV | | (0, 1) | Optimising |
| | Tension | T | Persons/(Protest * Persons) | (0, 1) | Auxiliary |
| | Tension velocity | TV | - | (0, 1) | Optimising |
| | Tension threshold | TT | - | (0, 1) | Optimising |
| | Legitimacy of measures | LM | - | (0, 1) | Auxiliary |
| | Mobility Residential | MBR | Change from baseline | # | Exogenous (Data) |
| | Mobility Workplaces | MBW | Change from baseline | # | Exogenous (Data) |
| | Morbidity due to disease | MR | Change from baseline | # | Exogenous (Data) |
| Mobilisation | Protests | P | Protest | # | Auxiliary |
| | Protests per citizen | PC | Protest/citizen | # | Constant (0.002/1000) |
| | Activists | CA | Persons | (0, CP) | Stock |
| | Mobiliation | CM | Persons/day | (0, CP) | Flow |
| | Disengagement | CD | Persons/day | (0, CP) | Flow |
| | Youth bulge | Y | Persons/Persons | (0, 1) | Exogenous (Data) |
| | Mobilisation tendency | TM | | (0, 1) | Optimising |
| | Mobilisation threshold | MT | - | - | Optimising |
| | Fatigue velocity | F | - | (0,10) | Optimising |

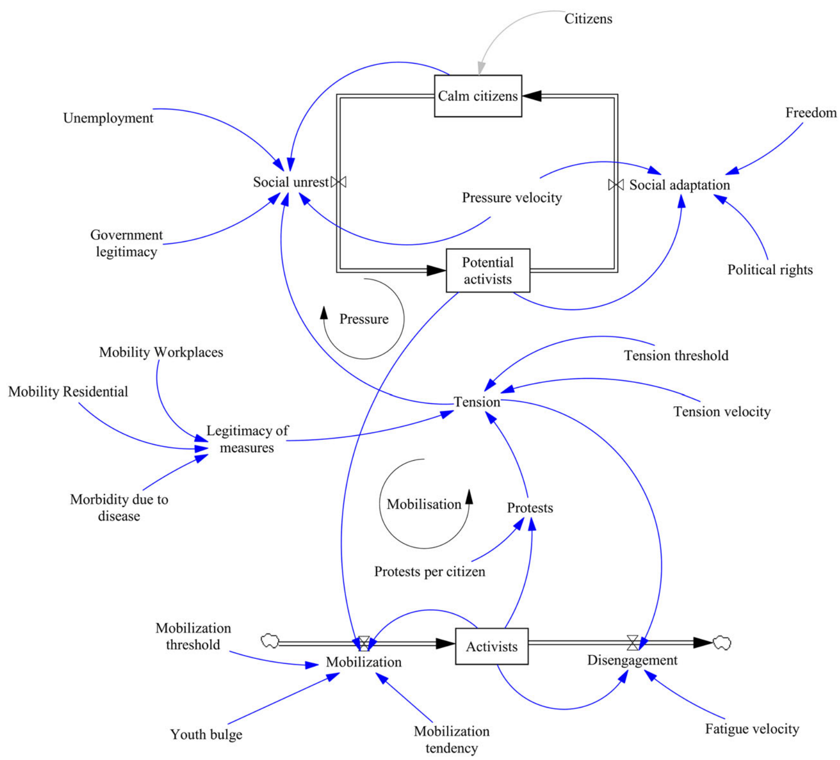


**Fig. 4 SDM model displaying two processes that explain the emergence of protests.** Variables are connected to display causal links. The tension resulting from the legitimacy of measures causes a shock to the system. The system encapsulates two feedback loops. The first feedback loop is the pressure process. The second feedback loop is the mobilisation process as a high level of tension that has a slowing effect on the disengagement process.

$$CD_{t+1} = e^{-T\times\frac{1}{F}} \times CA_t \tag{9}$$

$$P_t = CA_t \times PC \tag{10}$$

Next, we form Eqs. (3), (4), (5), and (6) to model a simplified dynamic to determine the number of dissatisfied citizens in a society, see Eq. (5). This process mimics tension as a pressure valve on the society, as it controls the number of potential recruits for civil resistance movements. As the level of tension is assumed to be zero at the start of the simulation, the total number of calm citizens is assumed to be equal to the population, see Eq. (3). The flow of calm citizens to potential activists (CU) is determined by the number of calm citizens that are effected by the tension. This number is calculated by multiplying number of calm citizens (CC) with the level of tension (T) amplified by the level of unemployment (U) and reduced by the level of legitimacy of the government (LG), see Eq. (4). The flow of potential activists to calm citizens is assumed to be steady, and influenced by the level of freedom and political rights, see Eq. (6). Furthermore, the pressure velocity (PV) parameter calibrates the velocity of both flow dynamics.

Lastly, we model the mobilisation process using Eqs. (7), (8), (9), and (10). As a starting point we use the model of Morozov et al. (2019). This model expresses mobilisation as a population dynamic in which current activists (CA) mobilise potential activists (CP). In our model, an increase of the number of activists thus increases the velocity of the mobilisation (CM), see Eq. (7). Once the level of current activists (CA) exceeds the mobilisation threshold (MT) times the maximum number of activists (CP + CA), the velocity of mobilisation stabilises at the level of mobilisation tendency (TM). This mobilisation tendency (TM) is an optimisation parameter, which indicates the average number of potential activists mobilised by each of the current activists. A parameter value above 1 would thus imply exponential growth of the civil resistance movement. The mobilisation of a group always starts with 1, thus the base level of activists is set at 1, see Eq. (8). The level of mobilisation is limited between the level of potential activists and the level of activists in order to ensure model consistency.

The disengagement of activists (CD) is modelled as a function of the fatigue velocity and tension, so that disengagement is high when tension is low and disengagement is low when tension is high, see Eq. (9). The number of protests is a function of the total number of activists, see Eq. (10), which simply assumes a linear relationship between the number of activists and the number of protests.

**Computational results**. The model was implemented in Vensim™ to explore the behaviour of the model, and to calibrate the six optimising parameters. Four countries were selected for calibration: Italy, Spain, USA, and the Netherlands. These countries were specifically selected as they experienced a large number of COVID-19 related protest events during the year 2020. The time step in the model was set to one day to match the scope of the data. The payoff function, parameter space, and explanation of the optimisation method are provided in S6.

Whilst optimisation of the model converged for the Netherlands and Spain, the model provides less explanation for the protests in the US and Italy. This can result from the differences between these countries. First, due to the size of the US, the dynamics of these variables could differ between states in the US, which could point to a specific maximum spatial scale for analysing this phenomenon. This implies that analysing the emergence of civil resistance using SDMs would require more detailed data in order to calibrate the population dynamics and better estimate the size of civil resistance movements. Second, the impact of the pandemic on tension can be different from one country to another. The combination of strictness of measures and excess deaths could provide a good explanation for the tension in Spain (excess deaths) and the Netherlands (high level of inhabitants per square metre ensures high mobilisation) and less for the other two countries. The immense impact of the disease upon fatality rates in Italy could have had a discouraging effect upon potential protesters in the initial phase of the pandemic. The increase of government legitimacy following strict public-health measures (Groeniger et al., 2021) demonstrates the necessity to distinguish these dynamics at an individual or group level in order to improve the generalisability of our model.

## Discussion

In this paper, we have presented a holistic approach for analysing the emergence of civil resistance during the outbreak of the COVID-19 pandemic. This approach builds upon promising efforts that attempt to quantify the potential of the outbreak of conflict for specific countries or regions (Chenoweth & Ulfelder, 2017; Goldstone et al., 2010; Hegre et al., 2019). We provide a framework to assess the contribution of disruptive dynamics on the emergence of civil resistance. Our analysis suggests that while incorporating variables that analyse fast changes in social systems could improve the understanding of when civil resistance might happen, incorporating variables that analyse slow developments of structural conditions might still be better estimates for the severity of such outbreaks. Additionally, the data analysis demonstrates the necessity to understand how societal conditions effect the underlying dynamics of civil resistance. The explicit modelling of temporal effects such as tension, recruitment, and disengagement enables to better understand temporal dependencies between socioeconomic conditions, interventions, and the emergent patterns. In our model, we make literature-based assumptions about underlying dynamics, which are effected by the incorporated factors. With this model, we are able to analyse the hypothesised interplay between the development of pressure in a society and mobilisation of civil resistance, enabling analysis of various feedback loops. The calibration of our SDM model yielded mixed results. While our model might provide a good explanation of the underlying dynamics in the Netherlands and Spain, less evidence was found for the dynamics in the US and Italy. As a result, our approach demonstrates the ability and methodology to evaluate the connection between societal conditions and characteristic dynamics of civil resistance movements, rather than a generalisable model of civil resistance movements.

Our modelling efforts are limited by some practical and theoretical constraints. In general, selecting relevant factors and extracting associated data to model societal tension is hard. Especially, identification of relevant factors that capture the emergence of political opportunity is hard due to changing perceptions. Our model limits these dynamics to changes in mobility, impact of the pandemic, and socioeconomic conditions. Owing to limited information in our data on the specific motivations for the protests, we were not able to distinguish different types of protests. For example, this could explain the poor fit of our SDM for the USA and Italy, as protests in these countries were potentially motivated differently. Capturing other issues, such as current legislation related to vaccination, could potentially further explain existing tension.

Additionally, we also rely on OECD data, which mostly limits our analysis to western, educated, industrialised, rich and democratic (WEIRD) societies, which limits the generalisability of our results. Moreover, the emergence of the Black Lives Matter movement could have had a interfering effect upon both civil resistance movements and media coverage. Bias in news-based event databases is well known (Mahoney, 2018).

The predictive power of models would possibly profit from several improvements in the granularity and quality of the data. Currently, our analysis is limited to the year 2020 as we rely on the ACLED data set for daily protest data. Most of the countries in our data set are only available at ACLED for this particular year and onwards. Future modelling efforts would profit from such detailed datasets over multiple years, as it would enable to analyse the effect of changes in slowly developing structural socioeconomic conditions upon the emergence of civil resistance within countries rather than between countries. Additionally, better estimates of the number of protest attendees in the datasets would enable to improve the precision of the modelling of mobilisation dynamics. While development of such datasets are taking place at ACLED and CCC, the current progress, quality, or scope of such datasets is insufficient to optimise models (Phillips & Pohl, 2021; Raleigh et al., 2010).

Combining other modelling approaches could be another way to improve predictive power. Two other modelling suggestions for modelling we identified along this project. First, approaches that allow to model individual changes of behaviour or attitudes would possibly enable to better explain the burstiness of protests. Modelling approaches such as agent-based modelling would enable to model such individual interactions that influence social contagion and behaviour change in a society, and provide more realistic models for mobilisation dynamics. However, these models require fine-grained datasets or detailed stylised facts of these dynamics. Second, news coverage on civil resistance movements and societal conditions, or the spread of disinformation could influence the way people perceive their environment and living conditions. Currently, our modelling approach only accounts for the change of behaviour in terms of mobility. Sentiment analysis of social media outlets, such as Twitter, would possibly provide a starting point for such analysis. Accounting for these dynamics would enable us to better understand the driving dynamics of civil resistance movements and underlying motivations for mobilisation. This in turn would allow policy makers and human rights institutions to anticipate upon societal instability and improve social cohesion.

## Data availability

The datasets analysed in this study are available in the Dataverse repository: https://doi.org/10.7910/DVN/2ZV4YZ.

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## Note

1 Austria, Belgium, Chile, Colombia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, United States

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## Competing interests
The authors declare no competing interests.

## Ethical approval
Ethical assessment is not required prior to conducting the research reported in this paper, as the present study does not have experiments on human subjects and animals, and does not contain any sensitive and private information.

## Informed consent
This article does not contain any studies with human participants performed by any of the authors.

## Additional information
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**Correspondence** and requests for materials should be addressed to Koenvander Zwet.