Supplementary Information

Appendix 1. Descriptive statistics

Variable	Statistic				
	Count	**Mean**	**Std**	**Min**	**Max**
Excess deaths (/100k citizens)	7726	0.27	0.52	-0.84	3.52
Population (100k)	7726	364.41	642.90	6.26	3283.01
Protest	7726	6.36	23.02	0.00	725.00
Riot	7726	0.42	2.18	0.00	96.00
Repression	7726	0.00	0.04	0.00	2.00
Protest COVID-19	7726	1.59	5.58	0.00	134.00
Riot COVID-19	7726	0.09	0.67	0.00	22.00
Repression COVID-19	7726	0.00	0.02	0.00	1.00
Unemployment	7726	0.07	0.04	0.02	0.21
GDP/capita (/10k)	7726	4.76	1.96	1.65	12.43
Factionalised elites	7726	0.38	0.18	0.11	0.76
Group grievance	7726	0.45	0.19	0.09	0.86
Economic inequality	7726	0.25	0.14	0.05	0.65
State legitimacy	7726	0.27	0.21	0.05	0.72
Containment measures	7726	0.53	0.17	0.00	0.82
Economic support	7726	0.59	0.30	0.00	1.00
Health care support	7726	0.52	0.17	0.00	0.84
Stringency index	7726	0.55	0.22	0.00	0.94
Public information campaign	7726	0.95	0.20	0.00	1.00
Retail change	7726	-0.23	0.26	-0.96	0.54
Grocery change	7726	-0.06	0.19	-0.94	1.62
Parks change	7726	0.41	0.75	-0.91	5.17
Transit stations change	7726	-0.29	0.22	-0.92	0.31
Workplaces change	7726	-0.25	0.20	-0.92	0.80
Residential change	7726	0.08	0.09	-0.14	0.46
Civil liberties	7726	0.89	0.10	0.58	1.00
Political rights	7726	0.91	0.09	0.68	1.00
Youth bulge	7726	0.17	0.03	0.14	0.26
Urbanisation	7726	0.77	0.11	0.54	0.98

Table 1. Descriptive statistics for data proxies

Appendix 2. Distribution of COVID-19 related protests per day

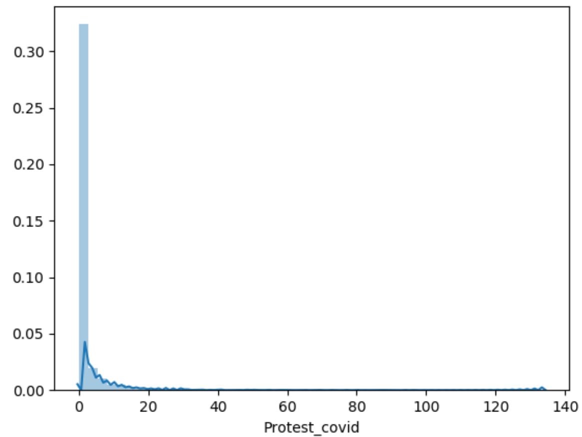

Figure 1. Distribution of protest per day

Appendix 3. ZINB models for fast variables

Four zero-inflated negative binomial regression models with the dependent variable of daily number of protests events related to COVID-19. The model variables are accompanied by regression coefficients with according significance, and standard error terms between parentheses. The variables are rolling average of a week (r), or lagged by a week (lag). All models include standard intercept and error terms. Furthermore all models include the excess deaths variable to measure the severity of the pandemic. Models are estimated using iterative maximum-likelihood-estimation (MLE). Model accuracy is compared by their AIC score.

	Dependent variable: Protest covid			
MODEL:	(1)	(2)	(3)	(4)
	Dissatisfaction	Opportunity	Mobilisation	Optimised
Intercept	-0.460***	-1.393***	0.267***	-0.900***
	(0.085)	(0.242)	(0.051)	(0.219)
Excess deaths per 100k r7	0.677***	0.308**	0.764***	0.325***
	(0.099)	(0.124)	(0.103)	(0.107)
Containment measures r7		6.141***		5.032***
		(0.565)		(0.523)
Economic support r7		-2.363***		-2.661***
		(0.217)		(0.253)
Residential change r7		-14.076***		-11.589***
		(1.972)		(1.172)
Retail change r7		-0.433		
		(0.542)		
Suppression covid r7			6.759	
			(4.180)	
Unemployment	8.874***			6.205***
	(0.944)			(1.172)
Workplaces change r7		-4.874***		-3.847***
		(0.585)		(0.581)
inflate Containment measures r7		-15.854***		-16.360***
		(0.964)		(0.905)
inflate Economic support r7		2.752***		3.117***
		(0.406)		(0.406)
inflate Excess deaths per 100k r7	-23.491***	0.762***	-17.205***	0.662***
	(3.445)	(0.203)	(2.732)	(0.184)
inflate Intercept	-2.328***	4.281***	-3.008***	5.563***
	(0.469)	(0.359)	(0.479)	(0.344)
inflate Residential change r7		-21.201***		-17.369***
		(4.061)		(2.207)
inflate Retail change r7		-1.340		
		(1.029)		
inflate Suppression covid r7			0.490	
			(125.424)	
inflate Unemployment	-20.378***			-15.784***
	(6.614)			(2.315)
inflate Workplaces change r7		-13.210***		-13.330***
		(1.162)		(1.055)
alpha	6.396***	2.952***	6.740***	2.801***
	(0.210)	(0.155)	(0.226)	(0.136)
Observations	6,238	6,111	6,208	6,177
Log Likelihood	-7843.3	-7345.1	-7918.4	-7312.3
AIC	15692.60	14824.11	15842.83	14638.69
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 2. ZINB models for fast variables

Appendix 4. Comparison between ZINB and NBM

Comparison of zero-inflated negative binomial regression model with a regular negative binomial regression model based on AIC value. Both model 5 and 6 are based on the same variables as model 4. The better accuracy of model 5 points to different processes that trigger protests related to COVID-19 and variables that determine the severity of the protests.

	Dependent variable: Protest covid	
	(5)	(6)
Intercept	-0.945***	-4.656***
	(0.232)	(0.172)
Excess deaths per 100k r7	0.439***	-0.207***
	(0.102)	(0.072)
Containment measures r7	5.354***	12.969***
	(0.568)	(0.433)
Economic support r7	-3.124***	-3.861***
	(0.270)	(0.177)
Residential change r7	-13.476***	-0.598
	(1.151)	(0.899)
Unemployment	8.739***	10.967***
	(1.341)	(0.844)
Workplaces change r7	-3.993***	3.487***
	(0.647)	(0.437)
inflate Containment measures r7	-16.202***	
	(0.942)	
inflate Economic support r7	2.355***	
	(0.526)	
inflate Excess deaths per 100k r7	1.139***	
	(0.228)	
inflate Intercept	5.660***	
	(0.357)	
inflate Residential change r7	-24.001***	
	(3.467)	
inflate Unemployment	-13.122***	
	(2.633)	
inflate Workplaces change r7	-14.391***	
	(1.136)	
alpha	2.935***	
	(0.152)	
Observations	6,194	6,231
Log Likelihood	-7220.7	-7521.8
AIC	14555.4	15057.5
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3. Comparison between ZINB and NBM

Appendix 5. NBM models for slow variables

Four negative binomial regression models with the dependent variable of daily number of protests events related to COVID-19. The model results of the three models are specified for variables accompanied by regression coefficients with according significance, and standard error terms between parentheses. The models include variables for demographics and economic factors, failed state index, freedom house index, all corrected for population. The models are optimised using Iteratively reweighted least squares (IRLS).

	Dependent variable: Protest covid			
MODEL:	(7)	(8)	(9)	(10)
	Dissatisfaction	Opportunity	Mobilisation	Optimised
Intercept	-1.751***	-5.737***	-0.696***	-2.088***
	(0.075)	(0.391)	(0.190)	(0.517)
Population 100k	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Civil liberties		-6.023***		
		(0.671)		
Group Grievance	-0.276*			
	(0.147)			
Political rights		10.180***		1.798***
		(0.779)		(0.444)
State Legitimacy		2.162***		1.909***
		(0.157)		(0.180)
Unemployment	9.978***			2.587***
	(0.595)			(0.730)
Urbanisation			1.596***	
			(0.247)	
Youth bulge			-9.439***	-8.453***
			(0.913)	(0.974)
Observations	6,242	6,155	6,205	6,203
Log Likelihood	-7535.2	-7275.8	-7733.9	-6916.6
AIC	15080.49	14563.64	15477.79	13947.12
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4. NBM models for slow variables

Appendix 6. Optimisation

Our SDM model inherits six parameters that enable to calibrate the behaviour of the model to our data set. In the optimization of our model we search for optimal values for these parameters for a specific country. We do so by fitting the model to the data about the number of protests in that particular country. In order to smoothen the burstiness effect of the number protests, we fit the model to a rolling average of the protests over 7 days. This also allows to correct the effect for specific weekdays (e.g. more protests on Saturday), which is not further investigated.

In the SDM, the number of is a function of the number of activists. The number of citizens, potential activists, and activists are modelled as 'stocks' of persons, and are a function of difference equations. The optimization parameters determine the velocity and thresholds of the transitions of persons towards one state to another. In order to optimize the model, we compare the outcome of our model with the number of protests in a given country. For the optimisation we create a vector of the six optimization parameters and create a payoff function using equation 10, which computes the number of protests in the SDM. A parameter space is set, based on the character of the equations (e.g. not more than 100% of the population can engage in the protests). This configuration for the first optimisation step is given in Table 7.

The optimisation of the estimated parameters follows a two-step procedure. In the first step, the Powell direction search method is implemented. This method minimises the payoff function using a bi-directional search heuristic[?]. The method escapes from some local optima as it restarts the optimisation process from various random points in the feasible parameter space. The Powell method is simple as it uses linear searches along the search vectors. The method is runs 100 iterations, in order to account for the possibility of multiple local optima. The search algorithm identified 3 to 6 local optima. The unique local peaks of the search method are stored for the next step. In the second step, a Markov chain Monte Carlo (MCMC) method is implemented in order to global optimisation and better quantify uncertainty. In order to minimise the influence of the curse of dimensionality, the parameter values of the local optima of step one are used for the MCMC. The MCMC applies differential evolution and randomised subspace sampling to simulate the distribution of the log likelihood payoff surface[?]. The algorithm performs a random walk on the likelihood surface of the payoff function in order to find minimum values. The Potential Scale Reduction Factor (PSFR) is used to assess the convergence of the model. The PSFR should be close to 1, and not exceed 1.2. Lastly, the optimising parameters are varied for 50% under and above the identified optimised value, whilst keeping other parameters constant. This enables to test the sensitivity of the model.

Variable	Min	Max
Tension Threshold	0	1
Tension Velocity	0	50
Pressure Velocity	0	1
Mobilisation Threshold	0	1
Mobilisation Tendency	0	2
Fatigue Velocity	0	10

Table 5. Parameter space for Powell Search Method

Country	Tension Threshold	Tension Velocity	Pressure Velocity	Mobilisation Threshold	Mobilisation Tendency	Fatigue Velocity	PSFR
Spain	0.0202	10.15	0.00008	0.015	1.079	0.7521	1.197
USA	0.1449	49.86	0.05870	0.312	1.977	0.0434	2.733
Italy	0.0108	15.74	0.00004	0.215	0.971	0.5059	2.455
the Netherlands	0.0131	12.10	0.00003	0.012	1.107	0.4375	1.159

Table 6. Optimisation results for each country

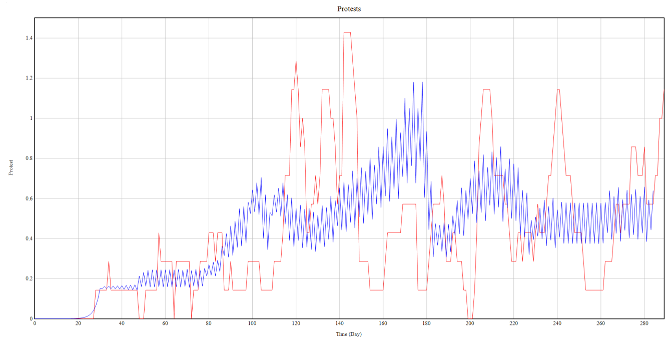

Figure 2. Fit of the model to the data for the Netherlands. Red line is a 7 day rolling average for the actual number of protests, the blue line is the simulated data for the optimised parameter setting.

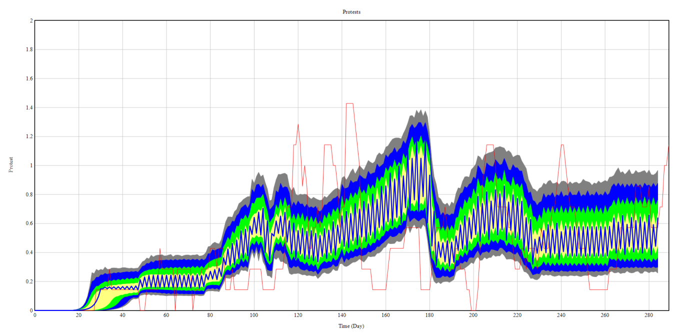

Figure 3. Sensitivity plot of the model calibrated to data of the Netherlands (red) with confidence intervals; 50% (yellow), 75% (green), 95% (blue), 100% (grey).