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A global threshold model of enabling conditions for social tipping in pro-environmental behaviours – the role of sea level rise anticipation and climate change concern

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Supplement

Robustness Checks of Macroscopic Approximation

Within this study, we utilize a macroscropic approximation of the threshold function, $F(r(t))$, representing the fraction of the contingent population (with relative size $p-a$) that takes part in a pro-climate change behaviour. This approximation is derived analytically (Wiedermann et al., 2020), assuming a Erdős–Rényi model for the unknown underlying social network (Erdős and Rényi, 1960).

Given that the true social network structure in any of the 66 countries simulated in this modeling exercise is unknown, we follow a logic akin to bayesian non-informative priors and use a Monte Carlo simulation approach, choosing a random average degree (K) and threshold value (ρ) for the macroscopic approximation, which results in an ensemble of sigmoid-shaped curves for the emergent threshold distribution (F) varying broadly in both the location and steepness of their inflection points. This approach thereby generates an ensemble of different shapes of F utilized in our simulations, including for example: (i) a step function (for large K and $\rho = 1$), (ii) an S-shaped curve (for intermediate K and ρ), (iii) a monotonic increase above the main diagonal for smallρ, and (iv) a monotonic increase below the main diagonal for large ρ. Hence different parameterizations are already considered when computing the total tipping potentials displayed in Figs. 3 and 5 of the paper. In that way, our approach is conservative in that it integrates widely across even qualitatively distinct forms of threshold functions as we do not make strong assumptions about any specific such form.

Notably, the Erdős–Rényi model is comparatively parsimonious and may not well represent more highly clustered network structures (Centola et al., 2018; Guilbeault and Centola, 2021). Accordingly, we engaged a series of robustness checks, comparing how well the ensemble of threshold functions emergent from our Monte Carlo simulations cover microscopic network dynamics across a range of network topologies: Barabasi-Albert (BA) (Barabási and Albert, 1999), Watts-Strogatz (WS) with rewiring probability $\beta = 0.25$ (Watts and Strogatz, 1998), a ring topology (Watts-Strogatz with $\beta = 0$), a Random Geometric Network (RGG) (Dall and Christensen, 2002) and real-world data from Facebook (63k nodes, avg. degree 26).

In general, we find that for all random topologies (Fig. S1), the ensemble of macroscopic approximations covers the empirical results from the above-mentioned additional micro-simulation models rather well when the certainly active nodes are sufficiently dispersed across the network. In other words, in most cases, there is a combination of ρ and K in the Erdős–Rényi network that produces an emergent threshold function F that is similar to what one would expect from certain other network topologies. In that sense, our Monte-Carlo approach can not only be interpreted as an ensemble of different Erdős–Rény networks, but an ensemble of different network topologies itself.

But, of particular note, when the certainly active nodes are closely clustered, we are less likely to observe tipping-like processes exemplified by this macroscopic approximation (esp. lower panel of Fig. S2). When the certainly active population is clustered within a highly modularized network structure, it is unlikely for the network to exhibit cascading processes resulting in social tipping across a broader population, as tipping would be contained to specific clusters and not penetrate through the network as a whole.

We suggest that in the case of anticipation of SLR, real-world social networks are less likely to have such highly modularized network structures. For many countries, SLR affects broad sections of coastlines, stretching across diverse social and geographic groupings. Furthermore, the effects of SLR are unlikely to be only observed and experienced by those directly impacted, rather these are likely to spill-over to broader geographic regions and social groups (e.g. through climate induced migration, mass media coverage) even though these are not specifically considered in the present manuscript. In such cases, we assume that a high clustering of the certainly active population within a modularized network structure is less likely to be representative of the actual network structure of the 66 countries simulated in this network-based threshold modelling exercise.

Further, for our research design, we explicitly chose a common level of complexity across all components. That is, the emphasis of these findings should not be too heavily on either the individual social, climate or network aspects, but rather the combined implementation of these factors. And this level of complexity is set at a lower-level to specifically allow for exploring conceptual scenarios. By keeping the modelling components on a relatively simplified level, we aim to avoid the tendency of assuming predictive capacity via the increased complexity of the modelling approach. In this case, we chose a macroscopic approximation of network topology that is comparatively simple, yet as we find, robust across a number of other potential structures.

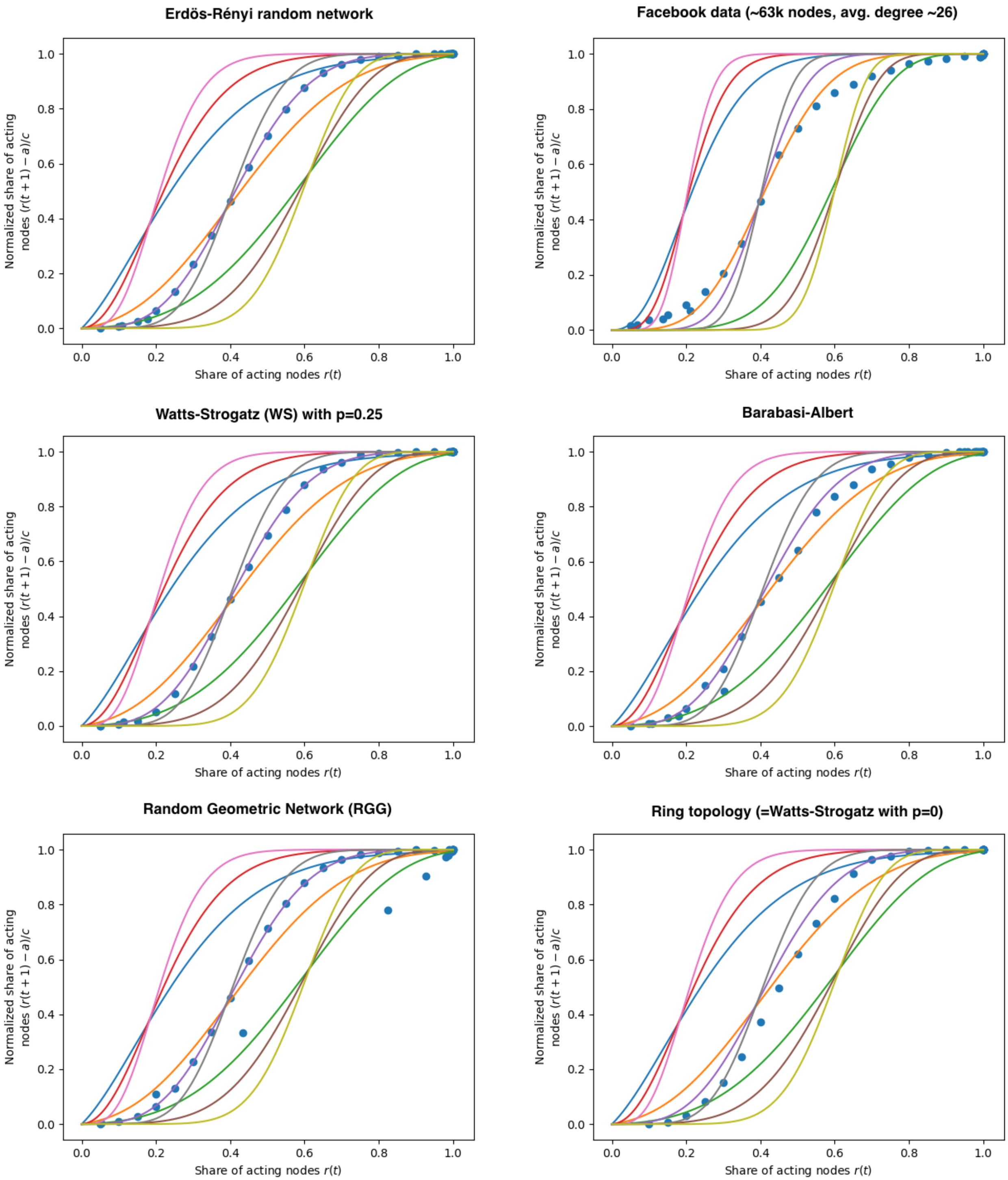

Figure S1. Robustness checks of macroscopic approximation - random network topologies. Each panel represents results from randomly chosen certainly active nodes across divergent network topologies. Each dot represents micro-simulations results, while the lines represent macroscopic approximations for nine exemplary combinations of the two parameters ρ and K – the actual ensemble contains a wider range of combinations.

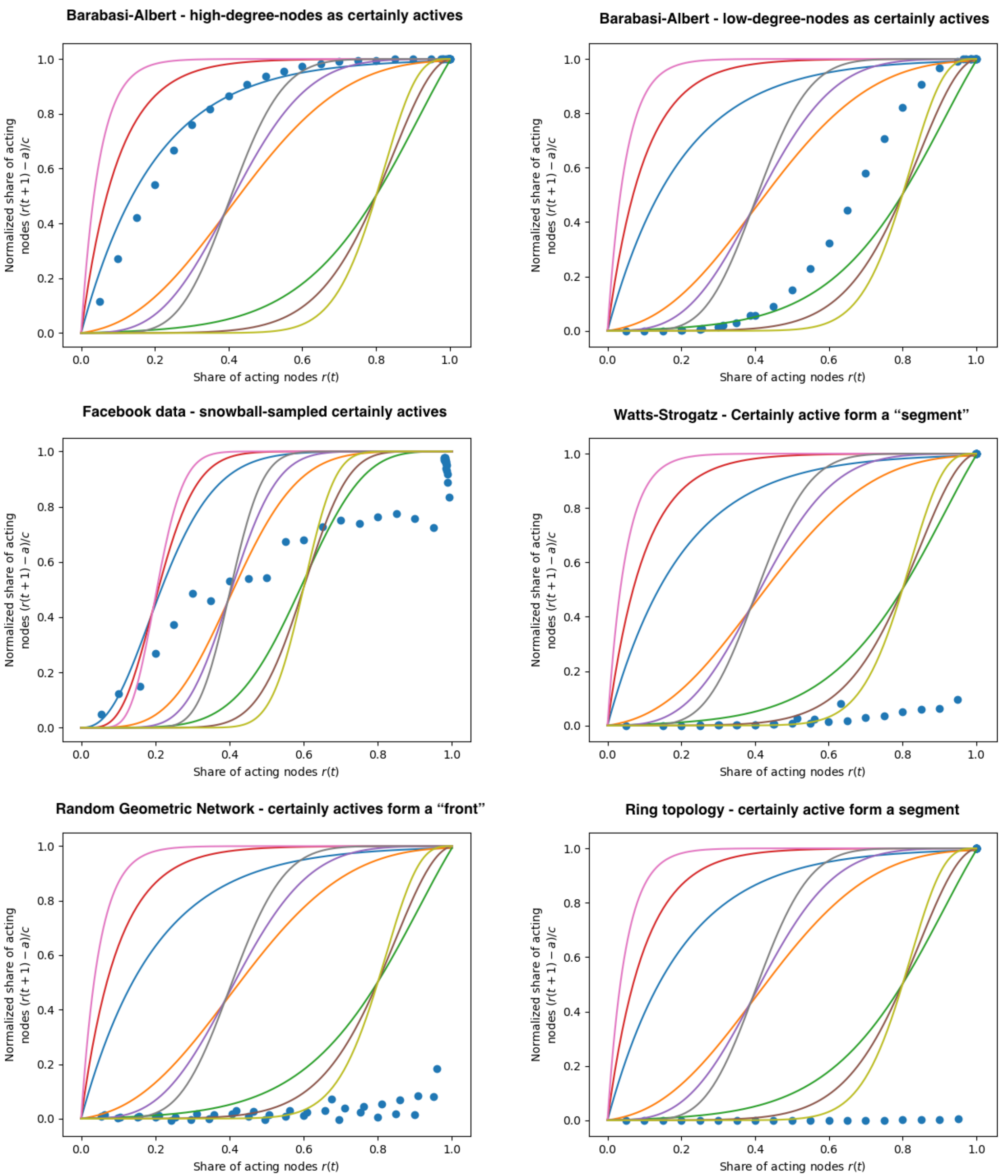

Figure S2. Robustness checks of macroscopic approximation - clustered, segmented and differential degrees in diverse network topologies. Each panel represents results from clustered, segmented and varied degrees of certainly active nodes across divergent network topologies. Each dot represents micro-simulations results, while the lines represent macroscopic approximations for nine exemplary combinations of the two parameters threshold rho and average degree K – the actual ensemble contains a wider range of combinations.

Data	**Year**	**Question Wording**	**Item Coding**	**Number of Outcomes n_s**	**Mean**	**Std. Dev.**
Eurobarometer *(EB 87.1 / EB 91.3)*	2017/ 2019	And how serious a problem do you think climate change is at this moment?	1 'Not at all serious' to 10 'Extremely serious'	10	0.75	0.05
ESS	2016	How worried about climate change?	1 'Not worried' to 5 'Extremely worried'	5	0.51	0.06
ISSP	2021	Do you think that a rise in the world's temperature caused by climate change is dangerous for the environment?	1 Not at a;; to 5 'Extremely dangerous'	5	0.74	0.04
IPOCC	2022	How worried are you about climate change?	1 'Not at all worried' to 4 'Very worried'	4	0.78	0.07
LITSII	2010	How concerned are you about climate change?	1 'Not concerned' to 5 'Extremely concerned'	5	0.58	0.08
PEW2015	2015	In your view, is global climate change a problem?	1 'Not a problem' to 4 'Very serious problem'	4	0.78	0.09

Table S1. Social Survey Data Sources, Question Wording, Items and Descriptive Statistics

Country	EB 87.1 2017	EB 91.3 2019	PEW Global Attitudes 2015	ISSP 2021	LITSII 2010	ESS 2016	Median
Albania	-	-	-	-	0.49	-	0.49
Argentina	-	-	0.83	0.76	-	-	0.80
Australia	-	-	0.71	0.58	-	-	0.64
Belgium	0.72	0.73	-	0.60	-	0.55	0.66
Brazil	-	-	0.94	-	-	-	0.94
Bulgaria	0.77	0.80	-	0.74	0.63	-	0.75
Canada	-	-	0.76	0.68	-	-	0.72
Chile	-	-	0.92	0.83	-	-	0.88
China	-	-	0.65	-	-	-	0.65
Croatia	0.73	0.74	-	0.75	0.65	-	0.73
Cyprus	0.78	0.82	-	-	-	-	0.80
Denmark	0.77	0.80	-	0.62	-	-	0.77
Estonia	0.59	0.64	-	-	0.48	0.41	0.54
Finland	0.71	0.72	-	0.63	-	0.51	0.67
France	0.78	0.80	0.82	0.62	0.50	0.55	0.70
Georgia	-	-	-	-	0.67	-	0.67
Germany	0.75	0.79	0.79	0.73	0.52	0.59	0.74
Ghana	-	-	0.86	-	-	-	0.86
Greece	0.81	0.84	-	-	-	-	0.83
Iceland	-	-	-	0.57	-	0.53	0.55
India	-	-	0.91	-	-	-	0.91
Indonesia	-	-	0.72	-	-	-	0.72
Ireland	0.71	0.77	-	-	-	0.44	0.71
Israel	-	-	0.63	0.70	-	0.42	0.63
Italy	0.80	0.80	0.82	-	0.68	0.55	0.80
Japan	-	-	0.76	0.79	-	-	0.77
Jordan	-	-	0.76	-	-	-	0.76
Kenya	-	-	0.84	-	-	-	0.84
Latvia	0.62	0.66	-	0.59	0.51	-	0.60
Lebanon	-	-	0.85	-	-	-	0.85
Lithuania	0.74	0.73	-	0.67	0.62	0.47	0.67

Table S2. Estimated shares of potentially acting individuals from weighted averages over all responses in the six survey programs. Dashes indicate that a country is not covered by the specific survey program. Countries with initial letters K–Z are found in Tab. S3

Country	EB 87.1 2017	EB 91.3 2019	PEW Global Attitudes 2015	ISSP 2010	LITSII 2010	ESS 2016	Median
Malaysia	-	-	0.76	-	-	-	0.76
Malta	0.77	0.86	-	-	-	-	0.82
Mexico	-	-	0.86	0.79	-	-	0.83
Moldova	-	-	-	-	0.74	-	0.74
Montenegro	-	-	-	-	0.47	-	0.47
New Zealand	-	-	-	0.60	-	-	0.60
Nigeria	-	-	0.85	-	-	-	0.85
Norway	-	-	-	0.57	-	0.50	0.53
Pakistan	-	-	0.71	-	-	-	0.71
Palestine	-	-	0.71	-	-	-	0.71
Peru	-	-	0.90	-	-	-	0.90
Philippines	-	-	0.89	0.75	-	-	0.82
Poland	0.68	0.74	0.64	-	0.53	0.43	0.64
Portugal	0.78	0.81	-	0.76	-	0.62	0.77
Romania	0.74	0.74	-	-	0.61	-	0.74
Russia	-	-	0.67	0.72	0.61	0.44	0.64
Senegal	-	-	0.80	-	-	-	0.80
Slovenia	0.75	0.77	-	0.69	0.62	0.55	0.69
South Africa	-	-	0.74	0.72	-	-	0.73
South Korea	-	-	0.79	0.73	-	-	0.76
Spain	0.80	0.83	0.80	0.75	-	0.60	0.80
Sweden	0.77	0.78	-	0.63	0.62	0.46	0.63
Taiwan	-	-	-	0.78	-	-	0.78
Tanzania	-	-	0.80	-	-	-	0.80
Turkey	-	-	0.73	0.81	0.55	-	0.73
Ukraine	-	-	0.67	-	0.62	-	0.64
United Kingdom	0.67	0.76	0.70	0.62	0.52	0.48	0.65
United States	-	-	0.66	0.61	-	-	0.64
Venezuela	-	-	0.89	-	-	-	0.89
Vietnam	-	-	0.88	-	-	-	0.88

Table S3. Same as Tab. S2 for countries with initial letters K–Z.

References

Barabási, A.-L. and Albert, R.: Emergence of Scaling in Random Networks, Science, 286, 509–512, https://doi.org/10.1126/science.286.5439.509, 1999.

Centola, D., Becker, J., Brackbill, D., and Baronchelli, A.: Experimental evidence for tipping points in social convention, Science, 360, 1116–1119, 2018.

Dall, J. and Christensen, M.: Random geometric graphs, Physical Review E, 66, 016 121, https://doi.org/10.1103/PhysRevE.66.016121, 2002.

Erdős, P. and Rényi, A.: On the Evolution of Random Graphs, in: Publication of the Mathematical Institute of the Hungarian Academy of Sciences, pp. 17–61, 1960.

Guilbeault, D. and Centola, D.: Topological measures for identifying and predicting the spread of complex contagions, Nature communications, 12, 1–9, 2021.

Watts, D. J. and Strogatz, S. H.: Collective dynamics of 'small-world' networks, Nature, 393, 440–442, https://doi.org/10.1038/30918, 1998.

Wiedermann, M., Smith, E. K., Heitzig, J., and Donges, J. F.: A network-based microfoundation of Granovetter's threshold model for social tipping, Scientific Reports, 10, 1–10, 2020.