Simulating the gaps

Using agent-based models to fathom opinion dynamics in panel studies

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Starting with failure

In a linkage study using a panel survey (3 waves, 1700 respondents) and parallel content analysis (10 newspapers), we tried to find an effect of media bias on public opinion in the run-up of a referendum campaign in Switzerland.

Table. Linear regression model explaining attitudes in wave 2 by wave 1 and media bias in individual media diet..

Variable	**B (SE)**	**p**
Previous Opinion	.732 (.032)	<.001
Individual Media Bias	.357 (.331)	.281
$R^2 = .483$		

Adding moderating effects, such as attitude certainty, media reliance, political orientation did not help. Media bias seemed to have no linear effect on individuals.
(except for right-wing arguments on authoritarian citizens Schemer et. al (2012))

Assuming more complex interactions

Media users don't get a total bias at the end of the month!

- They get coverage from their newspaper every day.
- They interact with other users of other newspapers
- They may be convinced on one day and pass their conviction to others
- On other days they are convinced by others

➢ These complex interactions may be modeled in an ABM

Uncommon usage of ABM

Initial state of all agents

Answers of respondents in Wave 1
(Attitude, Certainty, Media Use,
Media Reliance, Ideology…)

Final state of agents

Attitudes of respondents in Wave 2

Topography of the model

Media bias on each day
Attitudes of all other respondents

Rules of the model

Unknown

Finding reasonable rules

The social environment, consisting of media content and local opinion climate, leads to continuous attitudinal changes.

Quantification using social impact Theory (Latané, 1981):

ΔAttitude = Media Impact * Media Susceptibility + Social Impact * Social Susceptibility

Media Impact = Mean Pro/Con Bias in the news the Agent consumes on this day

Media Susceptibility = a_1 + b_1 * Attitude Certainty + b_2 * Media Reliance

Social Impact = Mean opinion of all other agents on this day, weighted by agent distance

Social Susceptibility = a_2 + b_1 * Attitude Certainty

Agent distance = b_3 * geographic distance + left-right ideological distance

$$\Delta A_{t,i} = \frac{\sum_m u_{(m,i)}(pro_m - con_m)}{N_m}(\alpha_1 + \beta_1 C + \beta_2 R) + \frac{\sum_j \frac{A_j - A_i}{\beta_3\left(\left(X_j - X_i\right)^2 + \left(Y_j - Y_i\right)^2\right) + \left(O_j - O_i\right)^2}}{\sum_j \frac{1}{\beta_3\left(\left(X_j - X_i\right)^2 + \left(Y_j - Y_i\right)^2\right) + \left(O_j - O_i\right)^2}}(\alpha_2 + \beta_1 C)$$

Finding optimal parameters

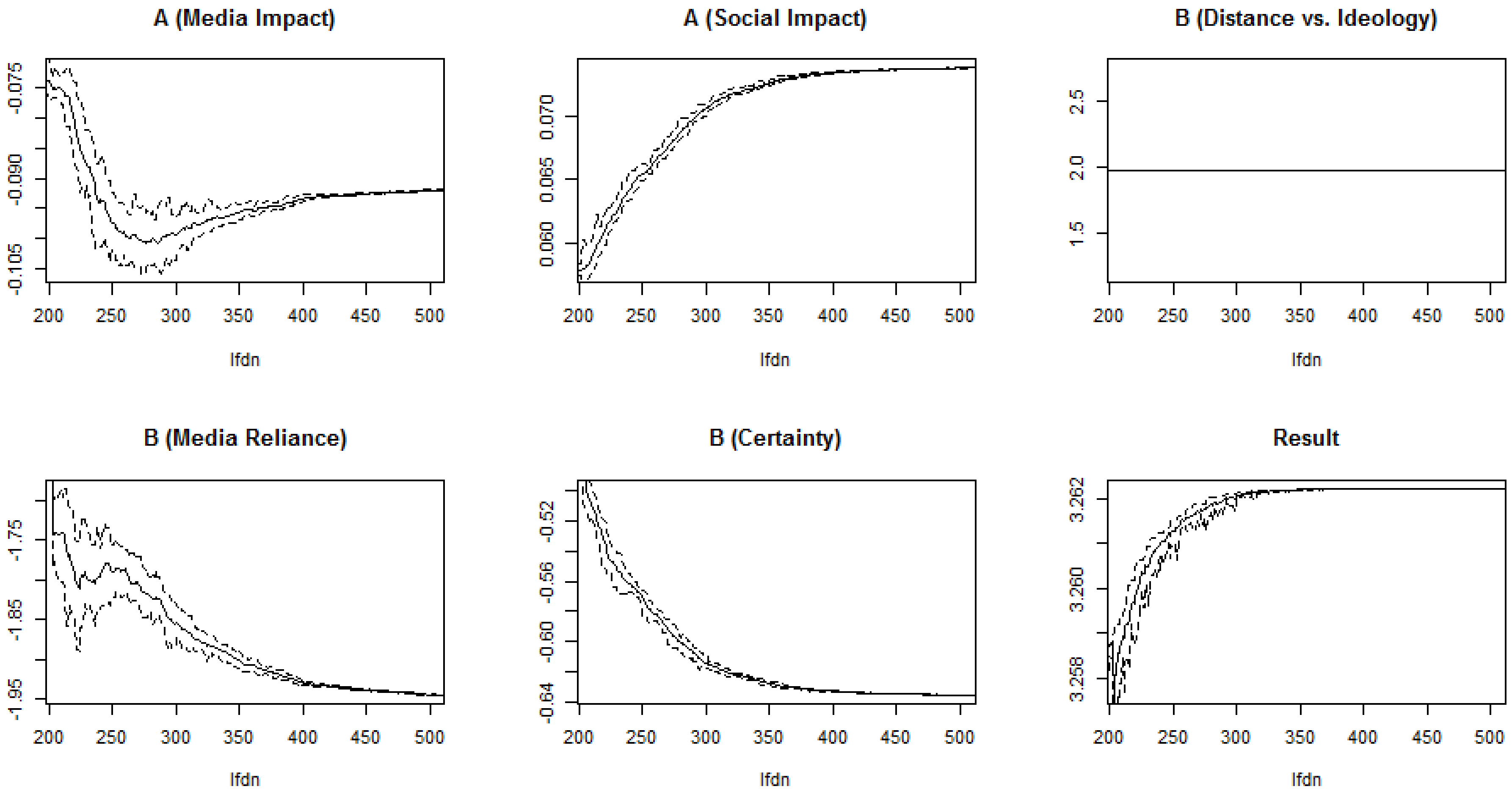
The parameters quantifying the susceptibility and the influence of certainty, distance, and reliance have to be estimated.

Evolutionary algorithm to determine optimal parameter configuration

1. Set prior means and standard deviations for each parameter.
2. Generate 30 different random parameter sets
3. Simulate using each set and compare the result to the second panel wave
4. Kill off 40% of the parameter sets which agreed worst. Allow for mutations in the rest.
5. Calculate posterior distribution of parameters
6. Generate new parameter sets based on posterior distribution to replace kills and old sets

Repeat for hundreds of generations.

Parameter progression



Main Findings

On actual study	On ABM for data analysis	On evolutionary Algorithms
Social impact (local opinion climate) is the most important predictor of attitude change.	The model performed better when taking into account all respondents, including panel drop-outs	Evolution takes time. Factors making it faster: • Increase selective pressure • Increase mutation rate • Keep legends alive
Media impact is stronger between waves 2 and 3. Between waves 1 and 2 it is only there for people with high media reliance.	Rules tend to become quite complex once you start. Try to keep it simple.	Close surveillance of progress is advised. EA may lead to absurd results in the absence of pressure.
The model explains 7-10% of attitudinal change. Linear regression models achieved below 1%.	There is only exactly 1 optimal solution for the sample. Use Bootstrapping to check for robustness of results.	Selective breeding may speed things up.

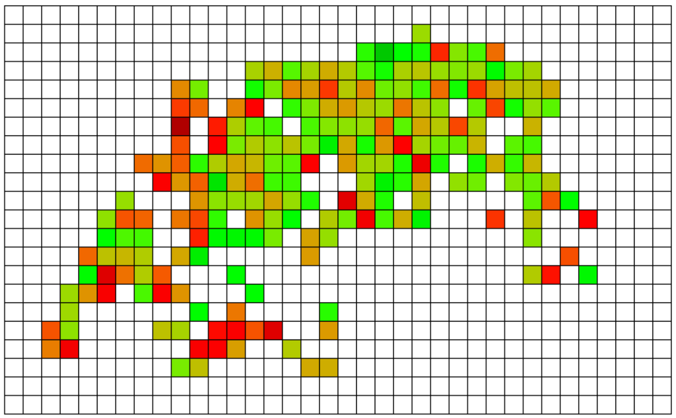
Thank you for your attention

Backup 1: Astonishingly simple python code

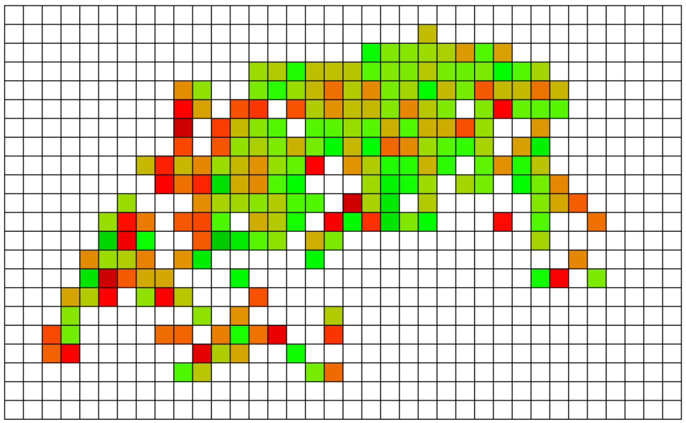
(Green: Evolutionary Algorithm, Blue: Simulation, Purple: Bootstrap)
Total 670 lines, including data management, maths functions and display of results

Backup 2: Real development and simulations

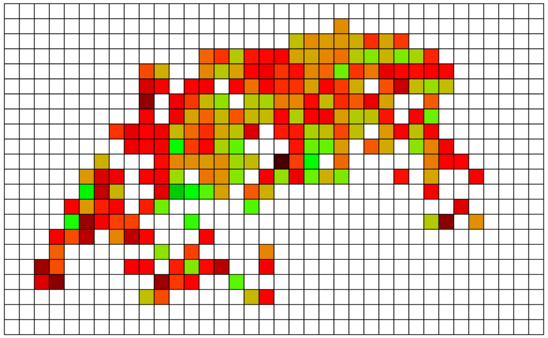
Wave 1



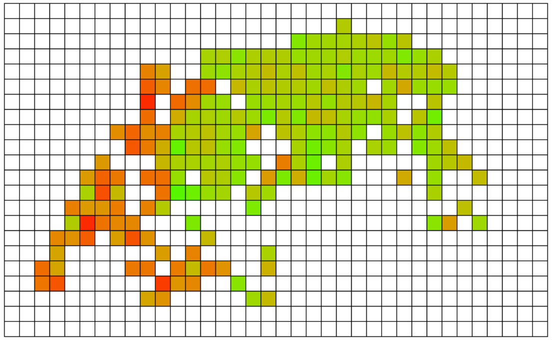
Wave 2



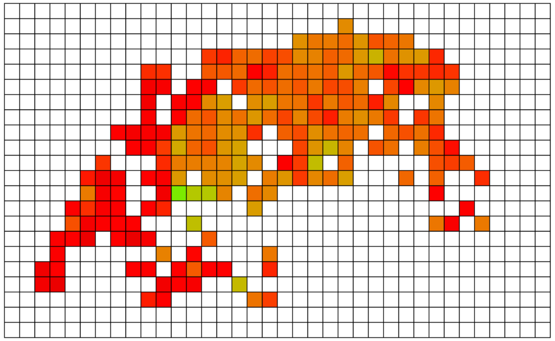
Strong media impact



Strong social Impact

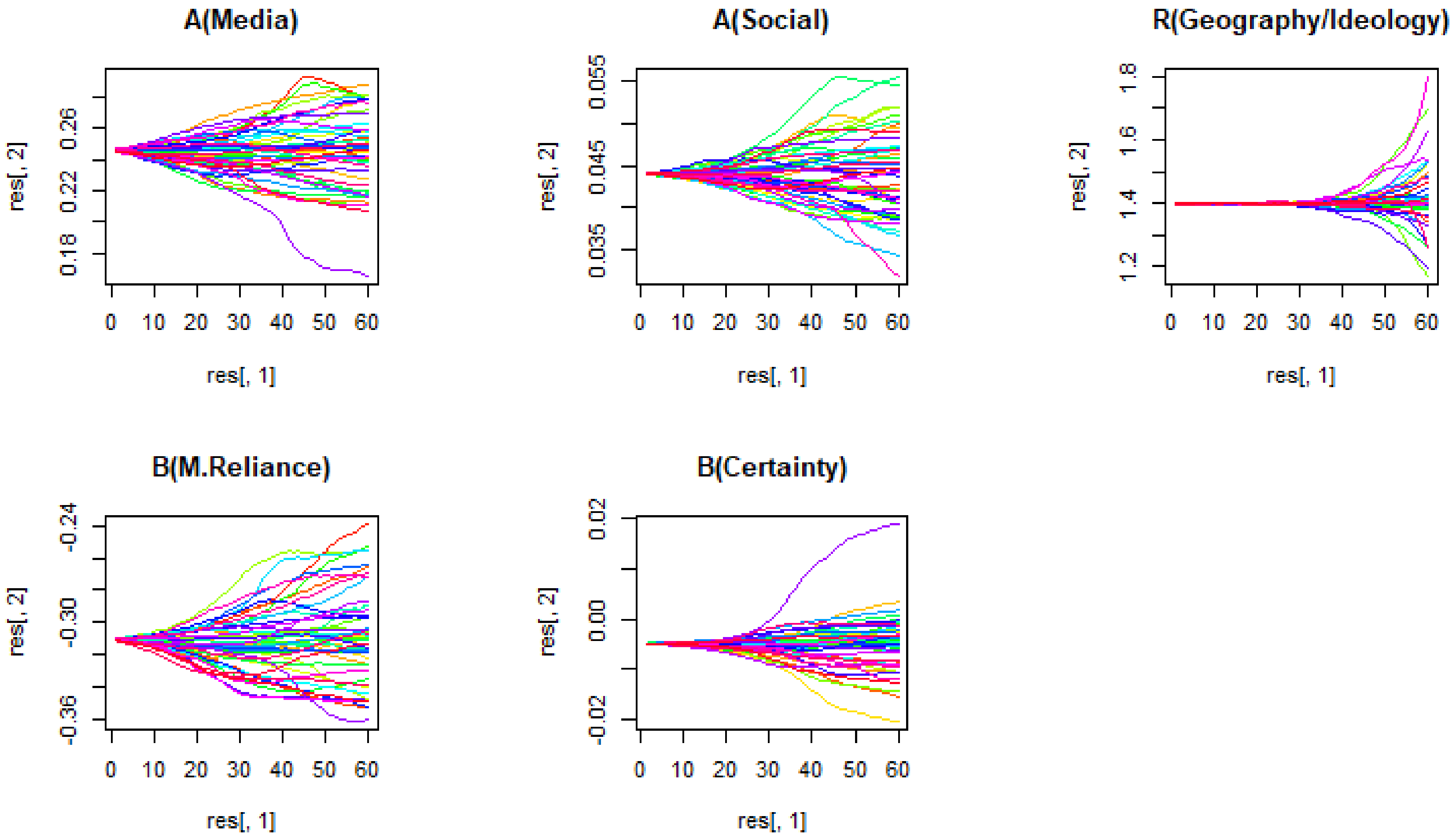


Both impacts strong



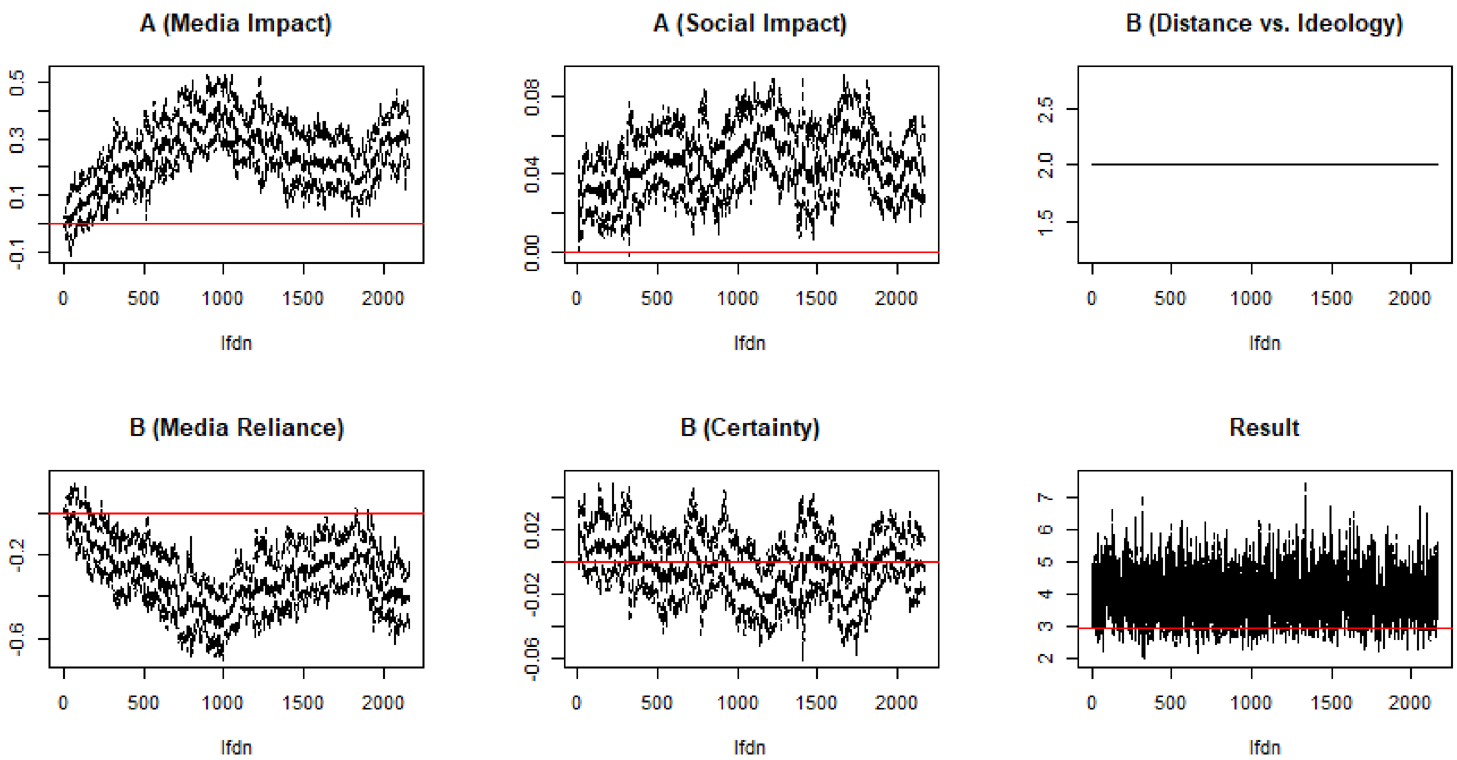
Bootstrapping of parameters

Using the parameters as priors for 50 additional evolutions for 60 generations

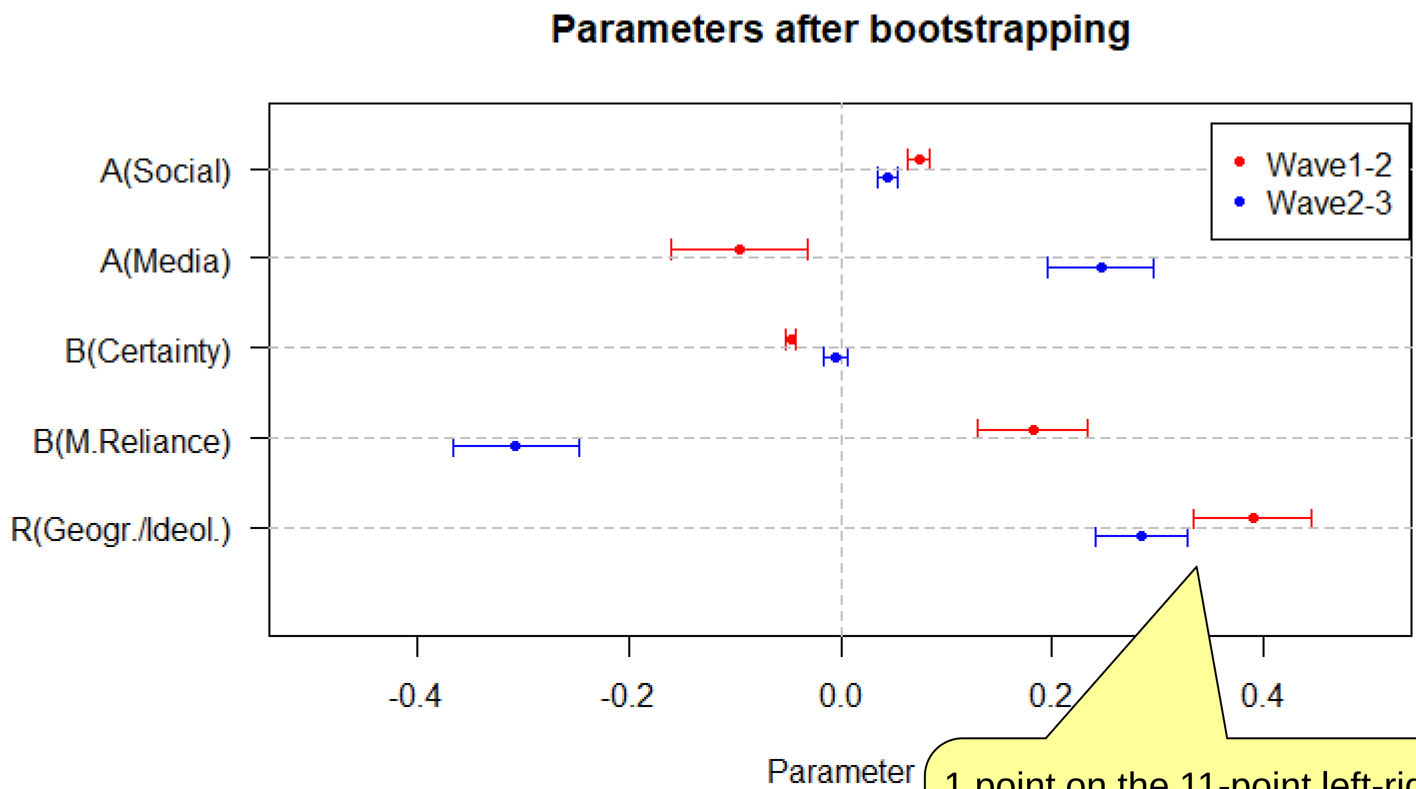


Bootstrapped evolution

For each generation of the EA, a new sample of agents was drawn



Optimal parameters and std. errors in both phases



1 point on the 11-point left-right scale corresponds to:
- 50km after the first wave
- 70km after the second wave

References

Latané, B. (1981). The Psychology of Social Impact. *American Psychologist*, *36*(4), 343–356.

Schemer, C., Wirth, W., & Matthes, J. (2012). Value Resonance and Value Framing Effects on Voting Intentions in Direct-Democratic Campaigns. *American Behavioral Scientist*, *56*(3), 334–352. https://doi.org/10.1177/0002764211426329