Online Appendix

A) Measurements:

Most important problem (MIP) question:

Q: "You will now be asked about the two most important political problems in Germany. If you think about the current political situation – what is, in your opinion, the most important political problem facing Germany today? Please only name the most important problem for now."

A: The response is recorded open-ended and later classified into 328 issues that I re-classified into 23 broader issues.

Second-most important problem (SMIP) question:

[Filter: Only those that mentioned one problem were asked]

Q: "In your opinion, what is the second most important political problem facing Germany today? Please only name one problem."

A: The response is recorded open-ended and later classified.

Newspaper use: BILD

"In election campaigns, there are many possibilities to get informed about the current political affairs in Germany. Let's start with daily newspapers. Do you read BILD regularly or sometimes, either the printed edition or the online edition? And on how many days in the past week have you read political news in BILD?"

0: Did not read. 1-7: Read on x days of the past week.

Newspaper use: Other newspapers

"Do you sometimes or regularly read any other daily newspaper, either the printed edition or the online edition?"

[A list of all newspapers included in the content analysis; up to two newspaper could be mentioned]

"On how many days of the past week have you read political news stories in that newspaper?"

0: Did not read. 1-7: Read on x days of the past week.

Television news use:

ARD news

"Let us now talk about TV newscasts. We start with the newscasts of the ARD, Tagesschau and Tagesthemen. On how many days in the past week have use watched Tagesschau or Tagesthemen, either TV or online?"

0: Did not watch. 1-7: Watchedon x days of the past week.

ZDF news

"And on how many days of the past week have you watched Heute or Heute Journal, the TV newscasts on ZDF, either on TV or online?"

0: Did not watch. 1-7: Watchedon x days of the past week.

RTL news

"And how about RTL aktuell, the newscast on RTL? On how many days of the past week have you watched this newscasts, either on TV or online?"

0: Did not watch. 1-7: Watchedon x days of the past week.

Sat.1 News

"And how about Sat.1 Nachrichten, the newscast on Sat.1? On how many days of the past week have you watched this newscasts, either on TV or online?"

0: Did not watch. 1-7: Watchedon x days of the past week.

B) Technical Description of Study Designs

I: Cross-sectional between design. (a) the aggregated (per issue i) issue salience of the public [$\bar{P}_i$] are regressed on the aggregated (per issue i) salience of the issue in the media [$\bar{M}_i$] at (b) only a single measurement period t_0. The unit of analysis would be the issues included in the study. So the number of cases equals the number of issues. The present study translates aggregate cross-sectional designs into hierarchical linear regression analyses with 69 cases: 23 issues recurring in 3 elections (2009, 2013, 2017); the model includes random intercepts for issues.

$$\overline{P}_i = \beta_0 + \beta_1 \overline{M}_i + (1|i)$$

II: Longitudinal between designs. Like in aggregate cross-sectional designs, (a) the aggregated (per issue i and time slice t) issue salience of the public ([$\bar{P}_{i,t}$]) are regressed on the aggregated (per issue i and time slice t) salience of the issue in the media (aggregated content analysis results [$\bar{M}_{i,t}$]). The number of cases equals *the number of issues × the number of time slices*. In terms of analysis, this design requires specific time series analysis techniques, e.g. to deal with potential autocorrelation and non-stationarity. The present study translates aggregate longitudinal designs into hierarchical linear regression analyses with 4554 cases: 198 measurement points for 23 issues. I add random intercepts for 23 issues nested in 3 elections. The fixed part of the model includes a lagged dependent variable (1 day lag) and time as a predictor to remove autocorrelation and ensure stationarity.

$$\overline{P}_{i,t} = \beta_0 + \beta_1 \overline{M}_{i,t} + (1|i)$$

III: Individual between designs. Individual between designs consider, (a) the individual issue salience of each respondent (disaggregated survey results [p_r]) are regressed on the amount of exposure to coverage about the issue the individual respondent has received (linked content analysis results [m_r]). This is done (b) for a single measurement period t_0 (that stretches out in the current study is the whole RCS period of 60 or 90 days per election; nevertheless, there is no repeated measure for the unit of analysis, the individual).

The present study translates individual level designs into hierarchical logistic-binary regression analyses with 495,351 cases: 21,537 participants (pooled across three separate elections) interviewed in the RCS wave about 23 issues. As each participant could only choose one issue, we did not include random intercepts for participant ID.

$$p_{r,i} = m_{r,i} + (1|i)$$

IV: Aggregate change designs. Aggregate change designs analyze how the aggregate-level change in public salience between two panel waves ([$\Delta\bar{P}_{i,t}$]) is predicted by aggregate-level media salience between two time slices ([$\bar{M}_{i,t}$]). This increases the number of units to *the number of issues × (the number of time slices dyads)*; in our case, that are 3 different elections that all had a two-wave panel study, resulting in one set of change scores per election: n=23×3=69. Again, time series methods can be used to analyze this type of data.

$$\Delta\overline{P}_i = \Delta\overline{M}_i + (1|i)$$

V: Individual change designs. Individual change designs consider (a) the intra-individual change in issue salience of each respondent (disaggregated survey results [$\Delta p_{r,i,t}$]) which are regressed on the amount of exposure to coverage about the issue I the individual respondent r has received between the two measurement periods (linked content analysis results [$m_{r,i,t}$]). I include the "t" even though there is only 1 change score (and hence only t=1), but multi-wave panel studies would have several change periods.

The present study translates individual change designs into hierarchical logistic-binary regression analyses with 313,352 cases: 13,624 participants interviewed in both waves (amounting to a change score) about 23 issues. As each participant could only choose one issue, we did not include random intercepts for participant ID.

$$\Delta p_{r,i,t} = m_{r,i,t} + (1|i)$$

Distributions of independent variables by design type: The distributions of the independent variables are implemented in the following ways for the five design types:

Design I: Arithmetic mean of exposure of the respondents to the issue *i* in the 14 days before the interview (as per the content-user link procedure). Theoretical range: 0-∞. Empirical range: 0-2.491/9.502/4.032/18.90. *M*=0.429/1.696/0.652/3.151. *Mdn*=0.195/0.852/0.241/1.571. *SD*=0.526/2.173/0.878/4.057.

Design II: Arithmetic mean of exposure of the respondents to the issue i in the 14 days before the interview (as per the content-user link procedure). Theoretical range: 0-∞. Empirical range: 0-6.942/28.785/10.816/54.709. *M*=0.500/1.983/0.767/3.664. *Mdn*=0.192/0.875/0.271/1.713. *SD*=0.719/2.866/1.142/5.182.

Design III: Respondents' exposure to the issue i in the 14 days before the interview (as per the content-user link procedure). Theoretical range: 0-∞. Empirical range: 0-32.167/63.913/46.957/120.886. *M*=0.787/3.381/1.320/6.839. *Mdn*=0.115/0.868/0.141/1.876. *SD*=1.750/6.608/2.905/12.895.

Design IV: Arithmetic mean of exposure of the respondents to the issue i between the two interviews (as per the content-user link procedure). Theoretical range: 0-∞. Empirical range: 0-5.376/16.762/7.344/33.052. *M*=0.862/3.236/1.296/5.708. *Mdn*=0.475/1.870/0.609/3.370. *SD*=1.081/3.832/1.640/6.821.

Design V: Respondents' exposure to the issue i between the two interviews (as per the content-user link procedure). Theoretical range: 0-1. Empirical range: 0-∞. Empirical range: 0-89.108/171.205/162.282/359.170. *M*=2.162/9.486/3.691/19.129. *Mdn*=0.286/2.090/0.503/4.470. *SD*=5.039/19.468/8.517/38.945.

The distributions are plotted in Figure A3.

Distributions of the dependent variables (aggregate/individual issue salience) by design type:

Design I: Theoretical range: 0-1. Empirical range: 0-0.567. *M*=0.074. *Mdn*=0.031. *SD*=0.116.
Design II: Theoretical range: 0-1. Empirical range: 0-0.730. *M*=0.074. *Mdn*=0.031. *SD*=0.117.
Design III: Theoretical range: 0-1. Empirical range: 0-1. Positive count (=1): 36,720. Negative count (=0): 458,631. Missing values count: 0.
Design IV: Theoretical range: 0-1. Empirical range: 0-0.258. *M*=0.019. *Mdn*=0.002. *SD*=0.051.
Design V: Theoretical range: 0-1. Empirical range: 0-1. Positive count (=1): 5,126. Negative count (=0): 288,835. Missing values count: 19,391.

C) Additional tables and figures

Table A1: Overview of study design types in agenda setting research

	Between data			Within data	
	Aggregate cross-sectional	**Aggregate longitudinal**	**Individual**	**Aggregate**	**Individual**
Survey design	Single cross-sectional	Multiple cross-sectional	Single or multiple cross-sectional	Panel survey	Panel survey
Media salience computation	Aggregated across media	Aggregated across media, by time slice	Raw	Aggregated across media, by time slice	Raw
Public salience computation	Aggregated across interviewees	Aggregated across interviewees, by time slice	Raw	Aggregated across interviewees, by time slice	Raw
Unit of analysis	Issue	Issue by time	Individual (by issue)	Issue by time	Individual by time (by issue)
Number of issues	Several	One or more	One or more	One or more	One or more
Function of time	Ignored	Define units of analysis, independent variable	Probably as independent variable	Define units of analysis, independent variable	Define units of analysis, independent variable
Media effect mechanism	Global exposure	Global exposure	Individual exposure	Global exposure	Individual exposure
Analysis method	Linear regression	Linear regression (with lagged DV)	Hierarchical binary logistic regression	Linear regression	Hierarchical binary logistic regression
Acapulco Typology Correspondence	Competition	Natural History	Automaton	—	Cognitive Portrait

Table A2: A Practical Example of content weighting for different individuals

Summary	Characteristics	Time frame	Enve-lope	Sali-ence	Media use	Total weight
Full effect	always used, highly salient, recent exposure	1.00	1.00	1.00	1.00	1.00
Moderate effect	Some use, some salience, relatively recent	1.00	0.80	0.80	0.80	0.51
Little effect	Rarely used	1.00	1.00	1.00	0.25	0.25
	Long ago	1.00	0.25	1.00	1.00	0.25
	Tiny story	1.00	1.00	0.25	1.00	0.25
	Less used, small story	1.00	1.00	0.50	0.50	0.25
No effect	False timing	0.00	0.00	1.00	1.00	0.00
	Virtually invisible	1.00	1.00	0.00	1.00	0.00
	Not used	1.00	1.00	1.00	0.00	0.00

Table A3: Intercoder agreement 2009-2017

	2009		2013		2017	
	TV	Print	TV	Print	TV	Print
	$\alpha_{Krippendorff}$	$\alpha_{Krippendorff}$	$\alpha_{Krippendorff}$	$\alpha_{Krippendorff}$	$\alpha_{Krippendorff}$	$\alpha_{Krippendorff}$
Polity	.57	.86	.22	1.00	.93	.88
Politics	.78	.81	.71	.77	.88	.85
Policy	.72	.83	.83	.74	.91	.89

Note. Numbers extracted from the method reports of the following data files:

GLES (2018). Wahlkampf-Medieninhaltsanalyse, Printmedien (GLES 2017). *GESIS Datenarchiv, Köln. ZA6809 Datenfile Version 1.0.0, https://doi.org/10.4232/1.13130.*

GLES (2018). Wahlkampf-Medieninhaltsanalyse, Fernsehen (GLES 2017). GESIS Datenarchiv, Köln. ZA6808 Datenfile Version 1.0.0, https://doi.org/10.4232/1.13186.

GLES (2015). Wahlkampf-Medieninhaltsanalyse, Printmedien (GLES 2013). *GESIS Datenarchiv, Köln. ZA5706 Datenfile Version 1.0.0, https://doi.org/10.4232/1.12293.*

GLES (2015). Wahlkampf-Medieninhaltsanalyse: Fernsehen (GLES 2013). *GESIS Datenarchiv, Köln. ZA5705 Datenfile Version 1.0.0, https://doi.org/10.4232/1.12173.*

GLES (2012). Wahlkampf-Medieninhaltsanalyse, Printmedien (GLES 2009). *GESIS Datenarchiv, Köln. ZA5307 Datenfile Version 1.0.0, https://doi.org/10.4232/1.11387.*

GLES (2015). Wahlkampf-Medieninhaltsanalyse, Fernsehen (GLES 2009). *GESIS Datenarchiv, Köln. ZA5306 Datenfile Version 1.2.0, https://doi.org/10.4232/1.12211.*

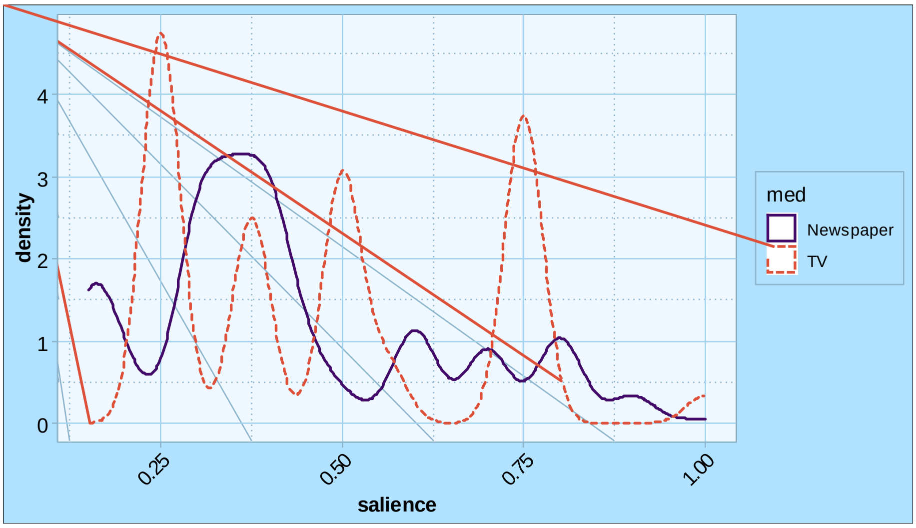

Figure A1: Distribution of the estimates of news story salience. While newspapers have many low-to-moderate salience news stories, TV news have many low salience and many high salience news stories. The reason is that TV news are often consumed completely while newspapers are used more selectively and hence of few news stories (those on the front-page, for example) have a high likelihood of contact with the reader.

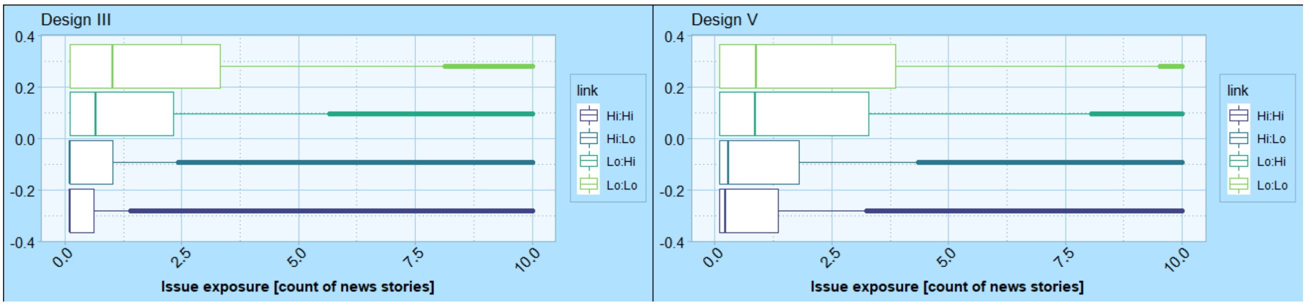

Figure A2: The distribution of individuals' exposure to news stories about an issue as a function of user-to-content link choices (here: design V). Low precision tends to lead to higher estimates of issue exposure. The reason is that, in the case of low precision, we lack the data to determine that much of the content has no or little chance to produce exposure.

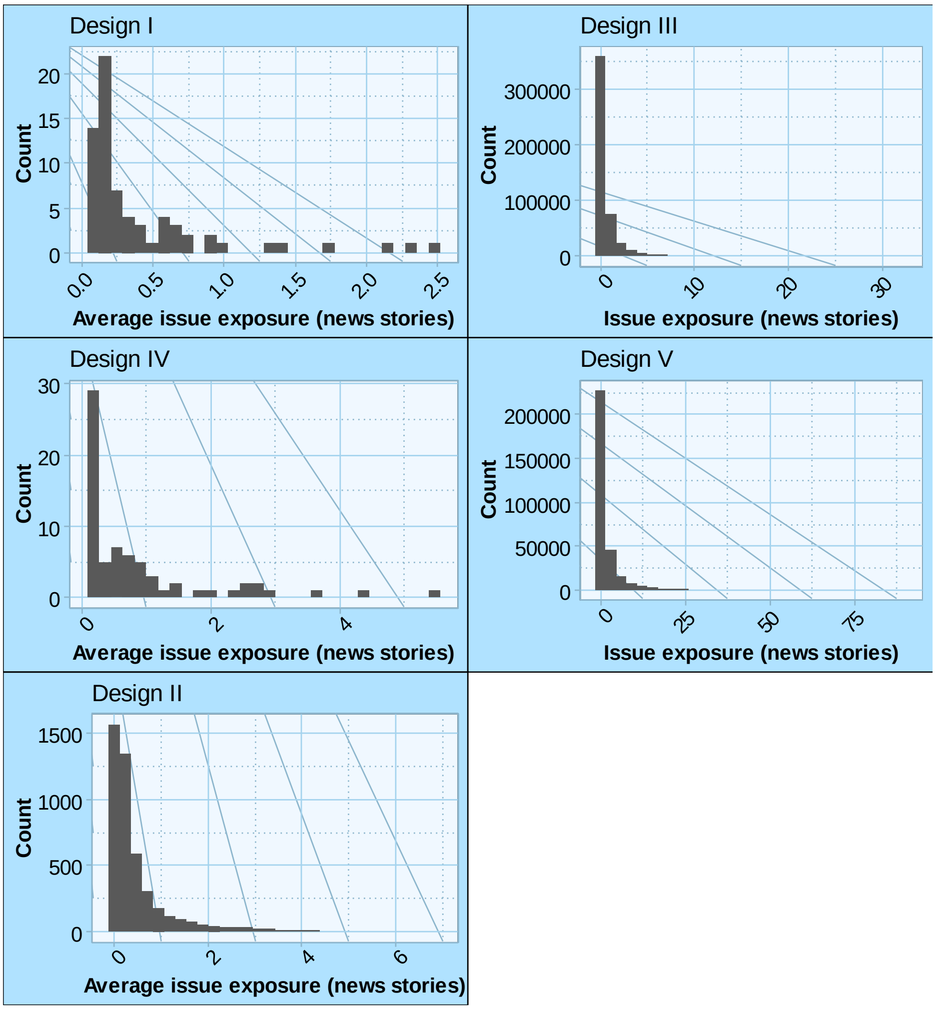

Figure A3: The distribution of individuals' exposure to news stories about an issue as a function of design.

The distributions of the dependent variables are plotted in Figure A4.

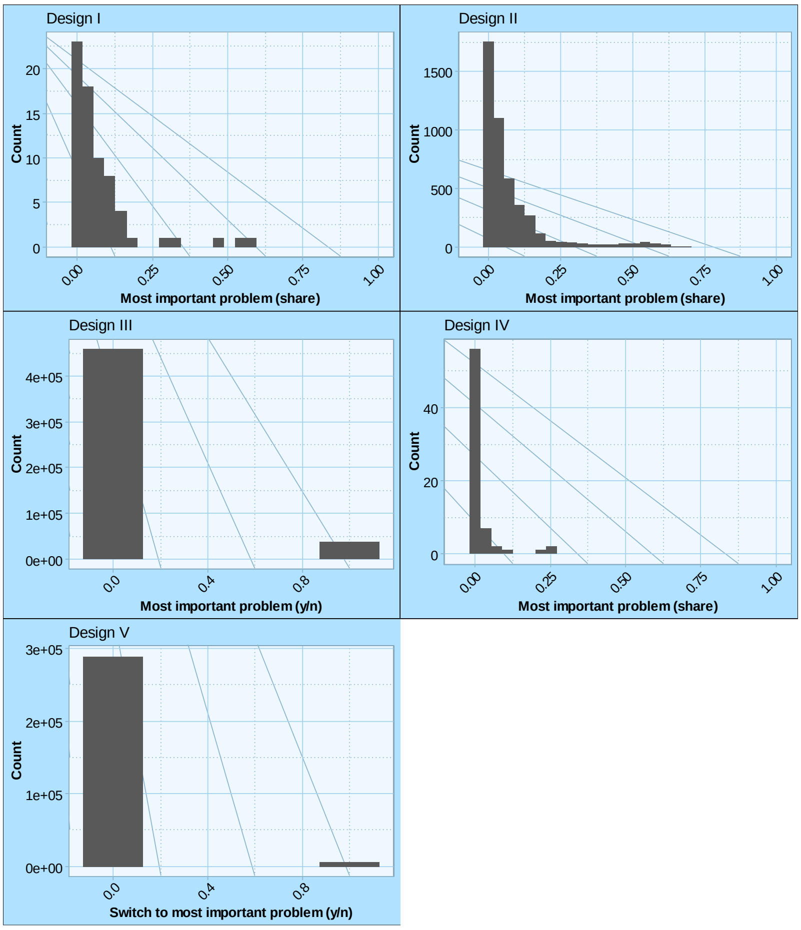

Figure A4: The distribution of the dependent variables in the five design types. The distributions are the same within each design type, independent of user-to-content linking.

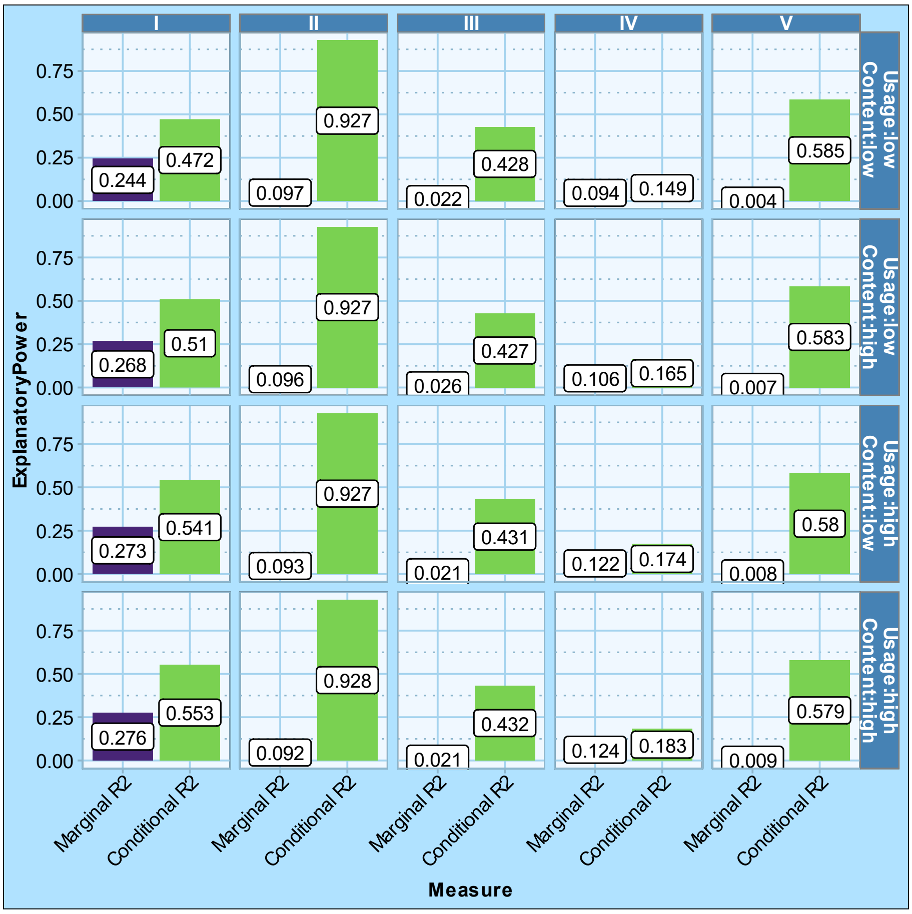

Figure A5: Explanatory power in the final model