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?”

[Filter: 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 you watched Tagesschau or Tagesthemen, either TV or online?”

0: Did not watch. 1-7: Watched on 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: Watched on 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: Watched on 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: Watched on 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.

\[
\bar{P}_i = \beta_0 + \beta_1 \bar{M}_i + (1|i)
\]

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 \( \times \) 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.

\[
\bar{P}_{i,t} = \beta_0 + \beta_1 \bar{M}_{i,t} + (1|i)
\]

III: Individual between designs. Individual between designs consider, (a) the individual issue salience of each respondent (disaggregated survey results \( p_{r,i} \)) are regressed on the amount of exposure to coverage about the issue the individual respondent has received (linked content analysis results \( m_{r,i} \)). 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 \( \Delta \bar{P}_i \) is predicted by aggregate-level media salience between two time slices \( \Delta \bar{M}_i \). This increases the number of units to the number of issues \( \times \) (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: \( n=23\times3=69 \).

Again, time series methods can be used to analyze this type of data.

\[
\Delta \bar{P}_i = \Delta \bar{M}_i + (1|i)
\]

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 \( \Delta m_{r,i,t} \)). 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.

\[ \Delta p_{r,ic} = m_{r,ic} + (1|i) \]

**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: \( 0-\infty \). 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: \( 0-\infty \). Empirical range: 0-28.785/10.816/54.709.  
\( M=0.500/1.983/0.767/3.664. \)  
\( Mdn=0.192/0.875/0.271/1.713. \)  
\( SD=0.719/2.866/1.142/5.182. \)

**Design III:** Respondents’ exposure to the issue \( i \) in the 14 days before the interview (as per the content-user link procedure). Theoretical range: \( 0-\infty \). Empirical range: 0-10.816/63.913/46.957/120.886.  
\( M=0.787/3.381/1.320/6.839. \)  
\( Mdn=0.115/0.868/0.141/1.876. \)  
\( SD=1.750/6.608/2.905/12.895. \)

**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: \( 0-\infty \). Empirical range: 0-5.376/16.762/7.344/33.052.  
\( M=0.862/3.236/1.296/5.708. \)  
\( Mdn=0.475/1.870/0.609/3.370. \)  
\( SD=1.083/3.832/1.640/6.821. \)

**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: 0-89.108/171.205/162.282/359.170.  
\( M=2.162/9.486/3.691/19.129. \)  
\( Mdn=0.286/2.090/0.503/4.470. \)  
\( SD=5.039/19.468/8.517/38.945. \)

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.  
\( M=0.074. \)  
\( Mdn=0.031. \)  
\( SD=0.117. \)

Missing values count: 0.

**Design IV:** Theoretical range: \( 0-1 \). Empirical range: 0-0.258.  
\( M=0.019. \)  
\( Mdn=0.002. \)  
\( SD=0.051. \)

Missing values count: 19,391.
### Additional tables and figures

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

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<thead>
<tr>
<th></th>
<th>Between data</th>
<th>Within data</th>
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<td></td>
<td>Aggregate longitudinal</td>
<td>Individual</td>
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<td></td>
<td>Individual</td>
<td>Aggregate longitudinal</td>
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<td>Individual</td>
<td>Individual</td>
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<td><strong>Media salience computation</strong></td>
<td>Aggregated across media</td>
<td>Aggregated across media, by time slice</td>
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<tr>
<td></td>
<td>Raw</td>
<td>Aggregated across media, by time slice</td>
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<td><strong>Public salience computation</strong></td>
<td>Aggregated across interviewees</td>
<td>Aggregated across interviewees, by time slice</td>
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<td></td>
<td>Raw</td>
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<tr>
<td><strong>Unit of analysis</strong></td>
<td>Issue</td>
<td>Issue by time</td>
</tr>
<tr>
<td></td>
<td>Individual (by issue)</td>
<td>Individual (by issue)</td>
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<tr>
<td><strong>Number of issues</strong></td>
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<td>Several</td>
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<tr>
<td></td>
<td>One or more</td>
<td>One or more</td>
</tr>
<tr>
<td><strong>Function of time</strong></td>
<td>Ignored</td>
<td>Define units of analysis, independent variable</td>
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<tr>
<td></td>
<td>Probably as independent variable</td>
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<td></td>
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<td>Linear regression (with lagged DV)</td>
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<td>Natural History</td>
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<td>Summary</td>
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<td>Time frame</td>
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<td>------------------</td>
<td>------------------------------------------------------</td>
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<td>Full effect</td>
<td>always used, highly salient, recent exposure</td>
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<td>Moderate effect</td>
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Table A3: Intercoder agreement 2009-2017

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<th>2013</th>
<th>2017</th>
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Note. Numbers extracted from the method reports of the following data files:


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