APPENDIX 1: THE BASIC PRINCIPLE OF MDS

As this is, to our knowledge, the first time that MDS is applied for the analysis of RTR and is not yet an established approach in debate research, we briefly explain the basic principles of the method hereafter.

The basic principle of MDS is that it extracts the relational structure between entities on the basis of information about their similarities and dissimilarities in a spatial representation, without requiring prior knowledge of the dimensions and their configuration. In this sense, it is a structure-identifying, inductive method and particularly suitable for explorative analyses, since it quantifies and visually displays (dis-)similarities of objects or characteristics.

The RTR data does not only provide information about the relation between participants and candidates. Rather the data also contain information on how (dis-)similar the study participants are to one another in terms of whether they agree in their evaluations to the statements by the candidates. With this information, the data can be used to extract and visualise the overall pattern of these (dis-)similarities in evaluation behaviour among the participants. This provides the opportunity to draw a common perceptual space of debate reception of the participants. The MDS is a convenient method to perform this analytical task. As such, we use metric multidimensional scaling that uses interval-scaled data and thus preserves the information about the size of intervals in the original dissimilarities in the generated distances. The procedure translates the raw (dis-)similarities for all pairwise comparisons between objects into spatial distances that can then be visualised in a low-dimensional space (Borg, Groenen and Mair 2012). The variation in the data is condensed in a way that the object scores on the extracted dimensions capture most of the original variance in the data. The lower the number of dimensions the greater is the information loss because more information has to be condensed. Ideally, the data can be summarised with only two dimensions that allow for a straightforward visual interpretation. This is more likely to be viable if the participants vary systematically regarding their RTR-evaluations. In that case, there is a larger pattern in the commonalities and contrasts between the participants that can be broken down to a few dimensions. Exactly this kind of patterning can be assumed to exist in political communication and competition where we hypothesise to find systematic ideological differences shaped by party identification. It is important to note that the dimensions that are extracted in the scaling analysis are merely products of the statistical procedure. They are extracted in such a way that they capture as much variation in the data as possible. They do, however, not have any inherent meaning.

In order to create the needed policy items for analysis, we dissected the debate into slices representing the respective candidates' speaking phases. Each phase ended five seconds after the person had ceased to speak in order to allow for slower votes to accumulate. All in all, we ended up with 48 speaking phases for Manfred Weber and 56 for Frans Timmermans. We then proceeded by summing up positive and negative votes a participant had cast within a given interval for the single statement of the respective candidate. These participant-by-item tables form the basis to compute our MDS-configuration.

When performing the MDS, we opt for a two-dimensional representation. We are confident that this configuration is adequate: First, the stress-I turns out to be very small. This value indicates the extent of information loss, but also allows for a straightforward and easily interpretable visual inspection using scree-plots. These graphs display the stress values for different numbers of dimensions that are used to represent the data to verify whether there is a leap in the loss of information when the number of dimensions is successively reduced (so called inverse-scree-test). As can be seen from the scree plot (Appendix 2) there is a clear elbow at two and three dimensions respectively. Considering the low stress-I-value and the simpler interpretation with a two-dimensional spatial representation, we regard this as an appropriate visualisation of the data. Additionally, the minimum criterion is met, according to which stress-I must be considerably below that for random proximities

(Borg 2010). The employed metric MDS uses interval-scaled information and thus requires that not just the ordering but also the size of all dissimilarities is taken into account when translating them into spatial distances (Borg, Groenen and Mair 2012).

Since the representation of all 157 participants prevents a straightforward interpretation and clutters the plot, we have condensed the RTR-data. For each item, we have calculated the average rating of a particular group, split by party identification. These form the basis for the positions in the MDS shown in figure 3. In order to investigate the more general reliability and distinguishability of these positions, we apply a bootstrapping algorithm to the scaling results, which makes it possible to obtain confidence intervals for the positions of the single partisan groups (Jacoby and Armstrong, 2014). In this procedure, the items that form the basis for the scaling are varied by random drawing with replacement n = 104 from the 104 items. This was performed with 1000 repetitions, resulting in reliability estimates for the positions in the form of confidence intervals (ellipsoids in a two-dimensional space).

The interpretation of the generated dimensions is a general challenge of the inductive scaling approach via MDS. It is important to note that the dimensions generated are solely products of the statistical method and are extracted in a manner that captures the maximum variation of the data on the interrelations between the single partisan groups - with dimension 1 explaining most of the variation and dimension 2 the second largest. However, they have no inherent meaning, and it is important to note that they do not form scales in the sense of dimensions derived from item inter-correlations. Rather, the meaning has to be reasonable on the basis of the group coordinates on these dimensions. Beyond that it is to be considered that the displayed main axes cannot always be interpreted directly. Instead, the dimension system can be rotated arbitrarily and inclined dimensions can span the space leading to a better interpretation of the solution than the main axes. This interpretation is facilitated by the familiarity with the visualised objects. In addition, one can take advantage of the fact that the raw data contain not only information about the (dis-)similarities between the partisan groups, but also information about their positions on the individual policy items. This original information can be used to determine the significance of the dimensions generated. By regressing the extracted dimensions (with the coordinates as values for the cases) to individual policy items, it is possible to understand how these items are linked to the extracted dimensions (Borg and Groenen 2005). The use of standardised coefficients from these regressions provides for the projection of vectors into the generated perceptual space. These vectors differ in their angle to the axes, depending on their relation to them.

APPENDIX 2: SCREE-PLOT