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Methodological Artifacts in Measures of Political Efficacy and Trust: A Multiple Correspondence Analysis

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Many authors report a positive relationship of education and political interest with political efficacy and trust, but it is well known that both of the former are associated with response styles, such as a tendency to "strongly agree." Since they are related to both a substantive concept (political efficacy and trust), and to methodological effects (agreement bias and a tendency to give non-substantive responses) it is important to assess whether the substantive relationship is due to methodological artifacts. Applying multiple correspondence analysis to the 1984 Canadian National Election Study, we will discuss a method which allows to test a set of items for measurement effects such as ordinality and response sets. In the given example, ordinality of the political efficacy and trust items could be confirmed only for politically interested respondents. For respondents with low political interest, there is clear evidence of a response set resulting in a tendency to "strongly agree" regardless of the direction of the items. Taken together, these findings call into question the substantive relationships reported in the literature.

1 Introduction

FEW RESEARCHERS WOULD deny that measurement issues are crucial to empirical analyses. Yet, as a recent paper on this topic notes, "Measurement effects and structural effects are so closely intertwined as to be nearly indistinguishable" (Jacoby 1999, p. 274). Our concern in this paper is to exemplify how multiple correspondence analysis can be used to expose measurement effects that might masquerade as structural relationships. To this end we reassess measures of political efficacy and trust since they occupy an important place in discussions about democratic theory and empirical research (Niemi et al. 1991; Stewart et al. 1992). Many studies focus empirically on these concepts, resulting in distinctions and refinements in the measures. For example, often applying structural equation models to the data, researchers distinguish between internal and external political efficacy and trust (see, e.g., Balch 1974; Craig and Maggiotto 1982). Regardless of the particular operationalization

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of political efficacy and trust, positive relationships of their measures with both "education" and "political interest" are generally reported (see Campbell et al. 1954; Finkel 1985; Parry et al. 1992; Hays and Bean 1993).

From a different body of literature it is also known that the same respondent characteristics ("political interest" and "level of education") are associated with the tendency to use nonsubstantive responses (see, e.g., Converse 1976; Faulkenberry and Mason 1978; Ferligoj et al. 1991; Hayes and Bean 1993; Thiessen and Blasius 1998; Mondak 1999). Such respondent attributes may also be operating for other response tendencies such as providing socially desirable responses and being prone to response sets. We intend to show that some of the substantive or structural relationships reported in the literature are arguably the result of such methodological effects.

As with the analysis of sets of survey items generally, measures of political efficacy and trust are fraught with numerous methodological difficulties. These include assessing ordinality, detecting response sets, and, where 5-point scales are used, determining the appropriate meaning of the middle (neither agree nor disagree) categories. Specifically, are they substantive or nonsubstantive responses?

The first issue we address concerns the level of measurement. Likert-type response formats are often treated as having ordinal or interval properties. When applying structural equation modeling, or other techniques requiring at least ordinal data, the ordinality of the items used is usually not assessed. Obviously, if ordinality does not hold, the solution will be ambiguous at best. We also address the detection of possible response sets in this paper. The battery of nine political efficacy and trust items that we use includes two whose polarity is reversed; that is, an "agree" response to one item implies a "disagree" response to another.

Furthermore, when 5-point Likert-type response alternatives are used, the meaning of the middle category is particularly problematic; it may be a substantive response between "agree somewhat" and "disagree somewhat." Alternatively, it may mean nothing more than the absence of an opinion. Individuals might feel that they are expected to hold opinions and therefore search for acceptable ways to mask their lack of an opinion. Some respondents may use equivocation (neither agree nor disagree) as a more acceptable alternative to admitting that they have no opinion.

We use data from the 1984 *Canadian National Election Study* (CNES) since it includes nine Likert-type items on opinions people held about the federal government (see Table 1 for the item wordings) to address the issues mentioned above.[1] For each statement respondents were asked if they "strongly agree," "agree somewhat," "disagree somewhat," or "strongly disagree"; in addition, they were given the opportunity to indicate that they had no opinion on the matter. The interviewer did not explicitly mention the "neither agree nor disagree" categories, but these were recorded as a middle category when volunteered by the respondent. This method of invoking the middle category suggests that "neither agree nor disagree" would most often be used by respondents who could not decide between "agree somewhat" and "disagree somewhat" when there are many pros and cons.

To explore the possibility that a sizable group of the population used the middle categories as a nonsubstantive response and to detect if subgroups have different *response patterns* (including methodological effects), we dichotomized the sample on the basis of political interest. To measure political interest, the individual mean of a set of items on

[1] The CNES is a large ($N = 3377$) multistage weighted probability sample; provinces with small populations are oversampled. Face-to-face interviews were conducted following the 1984 federal election exploring a number of social and political issues. The data are available through the Inter-University Consortium for Political and Social Research at the University of Michigan, Ann Arbor.

Table 1 Level of differentiation among items on political efficacy and trust ($N = 3355$)

Item	*Strongly agree*	*Agree somewhat*	*Neither agree nor disagree*	*Disagree somewhat*	*Strongly disagree*	*No opnion*	χ^2
a. Generally, those elected to parliament soon lose touch with the people.	**26.5**	**44.6**	**3.5**	**16.1**	**4.8**	**4.5**	
	28.4	44.3	3.9	13.4	3.2	6.7	94.9
	24.1	45.0	3.0	19.5	6.8	1.7	
b. I don't think the federal government cares much about what people like me think.	**27.0**	**32.9**	**3.8**	**24.2**	**9.0**	**3.2**	
	30.4	33.3	4.1	21.7	6.2	4.3	82.9
	22.7	32.3	3.4	27.4	12.4	1.8	
c. Sometimes federal politics and government seem so complicated that a person like me can't really understand wha't going on.	**31.0**	**33.1**	**2.4**	**19.0**	**12.6**	**1.9**	
	39.1	34.2	2.8	15.0	6.5	2.3	260.8
	20.6	31.6	2.0	24.1	20.3	1.3	
d. People like me don't have any say about what the government in Ottawa does.	**33.4**	**28.4**	**2.2**	**20.0**	**14.0**	**2.0**	
	38.4	29.1	2.7	16.6	10.3	2.9	118.6
	27.1	27.5	1.6	24.3	18.6	0.9	
e. So many other people vote in federal elections that it dosen't matter very much whether I vote or not.	**7.8**	**9.8**	**1.8**	**16.1**	**62.9**	**1.6**	
	10.5	12.4	2.1	19.5	52.9	2.6	193.7
	4.4	6.6	1.4	11.8	75.5	0.4	
f. Many people in the federal government are dishonest.	**10.5**	**25.0**	**10.1**	**24.6**	**18.3**	**11.5**	
	11.6	26.2	11.0	23.0	13.1	15.2	130.3
	9.1	23.5	9.1	26.6	24.9	6.8	
g. People in the federal government waste a lot of the money we pay in taxes.	**46.4**	**33.1**	**3.9**	**9.0**	**3.6**	**4.0**	
	46.3	33.7	4.6	7.3	2.6	5.5	55.3
	46.5	32.5	3.0	11.1	4.9	2.1	
h. Most of the time we can trust people in the federal government to do what is right.	**10.4**	**46.1**	**6.2**	**23.4**	**9.7**	**4.2**	
	8.6	47.2	7.5	22.3	8.8	5.7	51.4
	12.8	44.6	4.7	24.8	10.8	2.4	
i. Most of the people running the federal government are smart people who usually know what they are doing.	**16.0**	**45.4**	**5.9**	**21.0**	**8.2**	**3.5**	
	14.7	46.9	7.0	18.9	7.4	5.1	57.6
	17.6	43.5	4.4	23.7	9.2	1.6	

Note: Bold rows = total sample ($N = 3355$); Subsequent (2nd) rows = low political interest ($N = 1876$); Third rows = high political interest ($N = 1479$).

"political participation" (such as "reading newspapers," "watching programs," and "discussing politics"[2]) was used. Political interest was chosen as a control variable on the basis of its strong relationship both with political efficacy and with the tendency to give a nonsubstantive response such as "no opinion." The fact that political interest is related to both a *substantive concept* (political efficacy and trust) and a *methodological effect* (tendency to give a nonsubstantive response) raises the possibility that the former relationship is due to measurement artifacts.

2 Method

We use correspondence analysis (Benzécri et al. 1973; Gifi 1990; Greenacre 1984, 1993) to detect the structure of responses and to describe how the response categories of different items (including the "no opinion" responses) are related to each other and how they are related to additional information such as sociodemographic characteristics. The main objective of this method is to display rows and columns of contingency tables in two-dimensional spaces, called "maps." Since correspondence analysis has many parallels with principal-components analysis (PCA), we start with a brief overview of PCA.

Whereas PCA explores the structure of associations among a set of metric scaled variables, correspondence analysis explores the structure of associations among a set of contingency tables. Both methods produce underlying dimensions which can be interpreted as latent variables. Since correspondence analysis is applied to categorcial data and since in the social sciences the data are usually categorical, this method has a strong advantage over PCA. Input to correspondence analysis can be any data table with nonnegative values, such as a single contingency table, a stacked table,[3] a Burt table,[4] or an indicator matrix.

PCA consists of an eigenvalue decomposition of a symmetric matrix $\mathbf{R}$, which is either the correlation or the covariance matrix. This decompositon can be defined as the following product of matrices: $\mathbf{R} = \mathbf{B}\mathbf{\Lambda}\mathbf{B}^{\mathrm{T}}$, where $\mathbf{B}$ contains the eigenvectors of $\mathbf{R}$ in its columns and $\mathbf{\Lambda}$ is a diagonal matrix containing the eigenvalues in descending order, $\lambda_1 > \lambda_2 > \cdots > \lambda_m$, where m is the number of variables. The eigenvectors are normalized to the length of 1 and are orthogonal; this means that they satisfy the condition $\mathbf{B}^{\mathrm{T}}\mathbf{B} = \mathbf{I}$.

The idea of PCA is that a set of variables can be described as a linear combination of a smaller number of common factors. Given n cases and m variables, we can write $\mathbf{Z} = \mathbf{SL}$. The matrix $\mathbf{Z}$ contains either the mean centered variables (when analyzing the variance–covariance matrix) or the normalized (z-transformed) variables (when analyzing the correlation matrix). $\mathbf{L}$ contains the factor loadings, and $\mathbf{S}$ the factor scores. In a solution where the number of factors equals the number of variables, $\mathbf{Z}$ can be reproduced without error. Considering only the first k dimensions leads to a least-squares approximation of the data.

When $\mathbf{R}$ is the correlation matrix, we can compute $\mathbf{R} = (1/n)\mathbf{Z}^{\mathrm{T}}\mathbf{Z}$. The orthonormality of the factor scores is conventionally in the form $(1/n)\mathbf{S}^{\mathrm{T}}\mathbf{S} = \mathbf{I}$. It follows that $\mathbf{R} = (1/n)\mathbf{L}^{\mathrm{T}}\mathbf{S}^{\mathrm{T}}\mathbf{SL} = \mathbf{L}^{\mathrm{T}}\mathbf{L}$. Again, this solution is an approximation when fewer factors

[2] Response alternatives for each question ranged on a 4-point scale from "never" to "often." To retain a 4-point distinction for some of the analyses to be reported later, the sample was divided to correspond roughly in meaning to these 4 points.

[3] In the case of a stacked table we usually have one variable to be described and a number of describing variables. Input data are the row-wise concatenated frequencies of the cross-tabulations from the variable to be described with all describing variables.

[4] The Burt table contains all row- and column-wise concatenated cross-tabulations of variables included in the model, including the cross-tabulations of the variables with themselves. The Burt table can also be computed by multiplying the indicator matrix ($\mathbf{H}$) by itself ($\mathbf{H}^{\mathrm{T}}\mathbf{H}$).

than variables are used. If we rewrite the eigenvalue decomposition $\mathbf{R} = \mathbf{B\Lambda B}^{\mathrm{T}}$ as $\mathbf{R} = \mathbf{B\Lambda}^{1/2}(\mathbf{B\Lambda}^{1/2})^{\mathrm{T}}$, the factor loadings can be computed by $\mathbf{L} = (\mathbf{B\Lambda}^{1/2})^{\mathrm{T}}$.

Correspondence analysis translates deviations from the independence model in the contingency table into distances as the following brief introduction shows. Take any two-way contingency table with I rows and J columns and with frequencies n_{ij}. Dividing n_{ij} by the sample size n produces the percentages of the total p_{ij}, or, for the whole table, the $(I \times J)$ correspondence matrix $\mathbf{P}$; $\mathbf{r} = \mathbf{P1}$ is the vector of "row masses" or the "average column profile" with elements r_i, and $\mathbf{c} = \mathbf{P}^{\mathrm{T}}\mathbf{1}$ is the vector of "column masses" or the "average row profile" with elements c_j; $\mathbf{D}_{\mathrm{r}}$ and $\mathbf{D}_{\mathrm{c}}$ are the diagonal matrices of the row and column masses, respectively. The matrix of row profiles can be defined as the rows of the correspondence matrix $\mathbf{P}$ divided by their respective row masses, which can be written $\mathbf{D}_{\mathrm{r}}^{-1}\mathbf{P}$; for the matrix of column profiles this yields $\mathbf{PD}_{\mathrm{c}}^{-1}$. As a similarity measure between two row profiles (or between two column profiles, respectively), a weighted Euclidian or chi-square distance in the metric $\mathbf{D}_{\mathrm{r}}^{-1}$ (or $\mathbf{D}_{\mathrm{c}}^{-1}$, respectively) is used. For the chi-square calculations, the weighted deviations from independence over all cells of the contingency table are used. For each cell, the unweighted deviation of the observed from the expected value is calculated by $p_{ij} - r_i c_j$. In matrix notation, $\mathbf{P} - \mathbf{rc}^{\mathrm{T}}$ provides the unweighted deviations from the independence model for the whole table. To fulfill the chi-square statistic, this matrix is weighted by the product of the square root of the row and column masses to give the $(I \times J)$ matrix of standardized residuals $\mathbf{A}$.

$$\mathbf{A} = \mathbf{D}_{\mathrm{r}}^{-1/2}(\mathbf{P} - \mathbf{rc}^{\mathrm{T}})\mathbf{D}_{\mathrm{c}}^{-1/2}$$

Correspondence analysis computes a singular value decomposition of the matrix of standardized residuals: $\mathrm{SVD}(\mathbf{A}) = \mathbf{U\Gamma V}^{\mathrm{T}}$, where $\mathbf{U}$ contains the "left singular vectors," $\mathbf{V}$ the "right singular vectors," and $\mathbf{\Gamma}$ is a diagonal matrix with the singular values $\gamma_1 > \gamma_2 > \cdots > \gamma_{\mathrm{K}} > 0$ in descending order[5]. K is the rank of the matrix $\mathbf{A}$, and the columns of the matrices $\mathbf{U}$ and $\mathbf{V}$ are orthonormal; that is, $\mathbf{U}^{\mathrm{T}}\mathbf{U} = \mathbf{V}^{\mathrm{T}}\mathbf{V} = \mathbf{I}$. The close connection between the singular value decomposition and the eigenvalue decomposition is embodied in the following two results: $\mathbf{A}^{\mathrm{T}}\mathbf{A} = \mathbf{V\Gamma}^2\mathbf{V}^{\mathrm{T}}$ and $\mathbf{AA}^{\mathrm{T}} = \mathbf{U\Gamma}^2\mathbf{U}^{\mathrm{T}}$. The right singular vectors of $\mathbf{A}$ are identical to the eigenvectors of $\mathbf{A}^{\mathrm{T}}\mathbf{A}$, the left singular vectors are identical to the eigenvectors of $\mathbf{AA}^{\mathrm{T}}$, and the singular values of $\mathbf{A}$ $(\gamma_1, \gamma_2, \ldots, \gamma_{\mathrm{K}})$ are the square roots of the eigenvalues of $\mathbf{A}^{\mathrm{T}}\mathbf{A}$ or $\mathbf{AA}^{\mathrm{T}}$, respectively, that is, for example, $\gamma_1 = \sqrt{\lambda_1}$ (for more details, see Greenacre 1984; for the algorithm, see Blasius and Greenacre 1994).

The information from the singular value decomposition permits one to compute the row and column scores of each item category for all axes in the latent space. These values are the principal coordinates in the graphical displays: for the rows we obtain the $(I \times K)$ matrix $\mathbf{F}$, where $\mathbf{F} = \mathbf{D}_{\mathrm{r}}^{-1/2}\mathbf{U\Gamma}$; and for the columns we obtain the $(J \times K)$ matrix $\mathbf{G}$, where $\mathbf{G} = \mathbf{D}_{\mathrm{c}}^{-1/2}\mathbf{V\Gamma}$.

The maps drawn on the basis of these coordinates are called "symmetric maps." The distances between the rows and the distances between the columns can be interpreted as Euclidian distances, whereas the distances between the rows and the columns are not defined.[6]

[5]The singular value decomposition can be understood as the generalization of the eigenvalue decomposition. As shown by Eckart and Young (1936) the singular value decomposition is a least-squares method; for more details on this technique with respect to correspondence analysis, see Greenacre (1984).

[6]If one is interested in these distances, one has to rescale either the row coordinates or the column coordinates using the eigenvalues; these kinds of plots are called "asymmetric maps." There are some drawbacks to using these distances, too. Since the differentiation of the different kinds of maps is not important for this paper, we only refer to the literature (see, e.g., Greenacre 1984, 1993).

As in PCA, the input data can be factorized. Understanding correspondence analysis as a model (see, van der Heijden and de Leeuw 1985; van der Heijden et al. 1989, 1994), one can use the row and column coordinates for recomputing the input data. Adding the latent variables successively models the deviations from independency. This is similar to the loglinear model and other modeling approaches such as the latent class model and the log-multiplicative model (see, for example, Goodman 1986, 1991; van der Heijden et al. 1989, 1994). In loglinear analysis, for example, these deviations are modeled by using higher-order interaction effects; in correspondence analysis latent variables are used. Using the principal coordinates, for any cell

$$p_{ij} = r_i c_j \left(1 + \sum_{k=1}^{K} f_{ik} g_{jk} / \gamma_k \right)$$

or, in matrix notation,

$$\mathbf{P} = \mathbf{r}\mathbf{c}^{\mathrm{T}} + \mathbf{D}_{\mathrm{r}}\mathbf{F}\boldsymbol{\Gamma}^{-1}\mathbf{G}^{\mathrm{T}}\mathbf{D}_{\mathrm{c}}$$

The first part of the formula shows the independence model and the second part the modeling from independence by including the K latent variables in successive order. Including all K latent variables in the model fully reconstructs the data.

As in PCA, the first axis is chosen to explain maximum variation in the data, the second axis captures a maximum of the remaining variation, and so on. Again analogous to PCA, it is possible to interpret the variable categories in relation to the axes, which can be considered the latent variables. And furthermore, as in PCA and other data reduction methods, only the k major components are kept. The number of interpretable dimensions depends on criteria such as the eigenvalue criteria, theory (how many latent variables can be substantively interpreted), and the scree test (for more details, see Blasius 1994).

Whereas simple correspondence analysis is applied to a single contingency table or to a stacked table, multiple correspondence analysis uses the same algorithm on an indicator matrix. This is a matrix in which each response alternative of every variable included in the analysis has its own column. A "1" in a given column indicates that the respondent chose that response; otherwise there is a "0."[7] Taking as an example a simple cross-table with $I = 5$ rows, $J = 3$ columns, and $n = 300$ cases, input data in the simple correspondence analysis would be the frequencies of this cross-table. Turning to multiple correspondence analysis, input data are an indicator matrix with 300 rows (the number of cases) and 8 columns (the number of variable categories). Using the given example on political efficacy and trust with nine variables, each with six categories, every repondent has exactly five 0's and one 1 on every variable; the sum of each row is 9, and the sums of the columns give the marginal distributions of the items. Applying the indicator matrix to correspondence analysis captures all first-order interaction effects in the model, much like PCA does for metric data. Multiple correspondence analysis is also known under the names "homogeneity analysis" (see Gifi 1990; Heiser and Meulman 1994) and implemented in SPSS in the CATEGORIES module as HOMALS (SPSS Inc. 1990), "dual scaling" (Nishisato 1980, 1994), and "quantification of qualitative data III" (Hayashi 1980). Procedures to perform (multiple) correspondence

[7] An alternative to the indicator matrix as input to MCA is what is known as the Burt matrix. The solution from the indicator matrix can be directly converted to that of the Burt table by rescaling the solution; for example, the squared eigenvalues of the indicator matrix are those of the Burt table (see, e.g., Greenacre 1993).

analysis have been available since the late eighties in the major statistical packages such as SAS, BMDP, and SPAD.

As shown, correspondence analysis produces a latent space in which each response category of every item in the analysis can be located. Within the row categories and within the column categories, the distances can be interpreted as (dis)similarities of responses. Using the indicator matrix as input, response structures emerge when a significant number of respondents perpetually agree (or disagree) with a number of items or they consistently respond with "no opinion" or they consistently use the middle category. These categories will be close to each other in the latent space, whereas response categories that are relatively infrequently used by the same respondents are distant from each other.

Correspondence analysis employs the concept of inertia: the farther the categories are from the centroid along a given axis (squared distances) and the higher their masses (their marginals), the more the categories determine the geometric orientation of that axis. In the graphical solution, the locations of all variable categories can be compared to each other: short distances imply high similarities and long distances high dissimilarities. For all dimensions, correspondence analysis provides principal inertias which can be interpreted as canonical correlation coefficients (they are the singular values of the solution, the squared eigenvalues), correlation coefficients between the item categories and the latent variables, and scores for all item categories and all respondents (for more details in interpreting multiple correspondence analysis solutions, see Greenacre 1990, 1991; Le Roux and Rouanet 1998).

2.1 *Possible Outcomes*

Multiple correspondence analysis can be used for exposing different measurement effects that might masquerade as structural relationships. We briefly discuss possible outcomes giving different response structures. Given the explicit content of the nine items, the first dimension should capture the main item variation due to political efficacy and trust. Since previous research showed that internal and external political efficacies are highly correlated, all items should be associated with the first dimension. Distinctions between the two concepts might be mirrored in higher dimensions, but they are not considered in this paper. The items associated with the first dimension should retain their ordinality in the latent space. If they do not (if, for example, the locations of "strongly agree" and "agree somewhat" to a certain item are interchanged), one would have to question the reliability of the items. In the above example, the category with the lower value on the manifest variable has a higher score on the latent variable: expressing less trust in the federal government on the manifest item means having more trust in the federal government on the latent scale (assuming that all other items remain unchanged). Conceivably, this kind of interchange between successive categories might be meaningful if it occurred for only one or two variables, but not if it occurred frequently. Even worse would be interchanges across more than one category, as, for example, between "neither agree nor disagree" and "strongly disagree." Such a result would indicate that a substantial number of respondents failed to comprehend the questions.

The political efficacy and trust items combine an (assumed) ordinal measure on a 5-point scale and a "no opinion" response at the nominal level; the latter is usually excluded from the analysis. When using multiple correspondence analysis the "no opinion" responses can be included just like the other item categories. From the solutions, only the spatial positions of the 54 item categories are of interest; those of the 3377 respondents are ignored.

The Likert-type items can be treated as ordinal if the first dimension mirrors the order of the response categories of the manifest variables. Since "no opinion" is a nonsubstantive response, it should load on a higher dimension and be negatively associated with the

substantive responses on this higher dimension. If the "neither–nors" are nonsubstantive responses as well, and if respondents fluctuate between "neither–nor" and "no opinion" responses, then these respective item categories should be located close to each other and opposite to the substantive responses on the respective dimension. In a situation where the "neither–nors" are nonsubstantive, but respondents consistently choose either "neither–nor" or "no opinion," then both groups of item categories should be separated in the latent space, be uncorrelated with each other (with, say, one group of categories determined by the second and the other one by the third dimension), and be negatively associated with the substantive responses.

If the "neither–nor" responses are substantive, they should be located between "agree somewhat" and "disagree somewhat" and be negatively correlated with the nonsubstantive responses. If the "neither–nors" were used both as substantive and as nonsubstantive responses, these middle categories should be in their correct positions between "agree somewhat" and "disagree somewhat" on the first dimension. On the second (or a higher) dimension, either they can be positively associated with nonsubstantive responses (when fluctuating between the middle categories and the "no opinion") or they can be uncorrelated with the nonsubstantive responses (consistent use of "neither–nor" or "no opinion" responses).

If a substantial number of respondents did not pay heed to the direction of the questions, the responses to the two reversed items will not conform to an ordinal scale on the first dimension. The fewer the number of people who took note of the changed direction of the questions, the greater will be the disorder of categories along the first dimension. In contrast, if every respondent were cognizant of the changed direction, the order of response categories for these two items should be opposite that of the remaining items.

In addition to the possibility of visualizing the response structure, (multiple) correspondence analysis permits a distinction between *active* and *passive* (or *supplementary*) *variables* (or variable categories).[8] Only the former determine the geometric orientation of the axes in the latent space (for details see Greenacre 1984, 1993). In the given case we can construct the space on the basis of the political efficacy and trust items and we can describe how the structure of this space is associated with other variables. We will use supplementary variables to assess the findings in the literature which assert that politically less interested persons, as well as less educated ones, express less political efficacy and trust and are more likely to give nonsubstantive responses than respondents more interested in politics and/or well-educated persons. If our findings confirm these previous results, politically less interested persons (as well as less educated) must be relatively close to the "strongly agree" and "agree somewhat" responses on the first seven items (and to the "strongly disagree" and "disagree somewhat" responses on the last two items) as well as relatively close to the "no opinion" responses.

3 Results

Table 1 provides the marginal distributions of the nine political efficacy and trust items. The first line in each group (boldface print) provides the values for the whole sample; the second and third lines give the comparable figures for respondents with low ($N = 1876$) and high ($N = 1479$) political interest, respectively.

For the total sample as well as for both subgroups we find relatively low frequencies for the middle category. The coincidence between the use of the middle category and that

[8] To date, this feature is not available in SPSS HOMALS.

of "no opinion" is high; the lowest frequencies (item "e": so many other people vote in federal elections that it doesn't matter very much whether I vote or not) as well as the highest frequencies (item "f": many people in the government are dishonest) belong to the same items. This association is a first indication that "no opinion" and "neither agree nor disagree" were used for similar reasons.

Comparing the two subgroups reveals that respondents with low political interest consistently use the "no opinion" category more often than respondents with high political interest; the same holds, but to a lesser extent, for the "neither agree nor disagree" responses. Furthermore, respondents with low political interest seem to have less political efficacy and trust in the federal government; they are particularly likely to respond with "strongly agree" to the negatively formulated statements. For example, on item "c" (sometimes, federal politics and government seem so complicated that a person like me can't really understand what's going on), 39.1% of them gave this response, compared to 20.6% of their politically interested counterparts. Both findings are often reported in social science research: persons with little political interest and/or low education express less political efficacy and trust (Finkel 1985; Parry et al. 1992; Hays and Bean 1993), and they are more likely to give nonsubstantive responses (Francis and Busch 1975; Converse 1976; Faulkenberry and Mason 1978; Ferligoj et al. 1991; Thiessen and Blasius 1998; Mondak 1999). If we were to restrict our attention only to the marginal distributions, we would support the previous findings.

Although Table 1 shows significant differences between respondents with low and high political interest (see the chi-square values), this is not a sufficient basis for concluding that politically less interested people have less political efficacy and trust than others. It is necessary to analyze the structure of responses itself which may contain certain regularities that yield a greater understanding about the meaning of the responses.

The multiple correspondence analyses proceed in several steps. First, we focus on the total sample and then on the two subgroups. In the initial step we use information from all respondents (the number of cases without "missing questions," e.g., the interviewer forgot to ask this set of questions) to apply correspondence analysis to the (3355×54) indicator matrix. Examining the eigenvalues (the squared singular values), the value of the first dimension is $\lambda_1 = 0.335$ (6.7% explained variances), the second is $\lambda_2 = 0.318$ (6.4%), and the third is $\lambda_3 = 0.249$ (5.0%). The drop between the second and the third values indicates that the two-dimensional solution is appropriate.[9] The graphical solution of the first two dimensions is given in Fig. 1.

Figure 1 shows that the first dimension captures the degree of political efficacy and trust in the federal government. Projecting the values of the nine Likert-type items onto this axis, the left part is occupied by "strongly agree" (except the values indicated by an asterisk—these are items "h" and "i," whose polarity is reversed), the right part mainly by "disagree somewhat," and the part still farther to the right, "strongly disagree." The locations of the numbers, where 1 stands for "strongly agree" and 5 for "strongly disagree," suggest that the items have an ordinal measurement level.[10] The middle categories ("3") are at their ordinally correct locations on the first axis, but they are also situated on the positive part of

[9] Without discussing statistical details, it can be shown that the amount of explained variances attributable to the first several axes has been underestimated (see Greenacre 1988). However, we forgo recomputing the explained variances since the decreasing order of the axes including the variable categories belonging to them is retained; differences between the maps using several adjustments are so small that they can be ignored.

[10] Please note that this is an aggregate interpretation; for reasons of readability we do not show the locations of the individual item categories at this stage of the analysis.

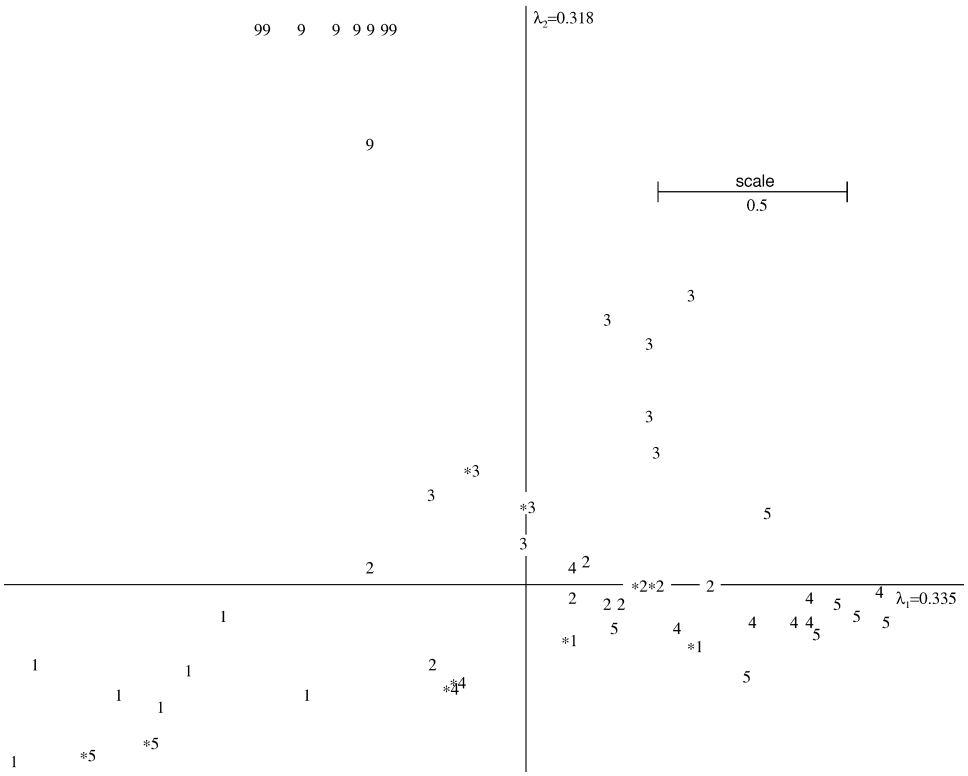

Fig. 1 Multiple correspondence analysis of political efficacy and trust. (1 = strongly agree, 2 = agree somewhat, 3 = neither agree nor disagree, 4 = disagree somewhat, 5 = strongly disagree, 9 = no opinion.)

the second axis, opposite the substantive values "strongly agree" to "strongly disagree."[11] The "no opinion" responses ("9") are also located on the positive part of the second axis (to improve the readability of the display, the "no opinion" locations for eight of the nine items were moved toward the center without overlapping on the horizontal axis). The positions of the middle categories and the "no opinions" on the second axis indicate some alternating use of "no opinion" and "neither agree nor disagree."

Additionally, the global ordering of the categories seems satisfactory, including those with reversed polarity. The second dimension reflects the expected differences between nonsubstantive responses (located on the positive part) and substantive responses (located on the negative part). With respect to the "neither–nors," which are correlated with both dimensions, it seems that there are two overlapping effects: the middle categories were used to express real opinions and to mask nonsubstantive responses.

In the next step we analyze the associations of this response structure with a number of respondent attributes, treated as passive variables. We include those variables that have been found to be related to political efficacy and trust and to the tendency to give nonsubstantive responses. These are "sex" (abbreviated "F" and "M"), "age" (subdivided into six categories:

[11] The proximity of the substantive responses to the centroid on the second axis can be explained with geometric properties in multiple correspondence analysis (see, e.g., Greenacre 1984).

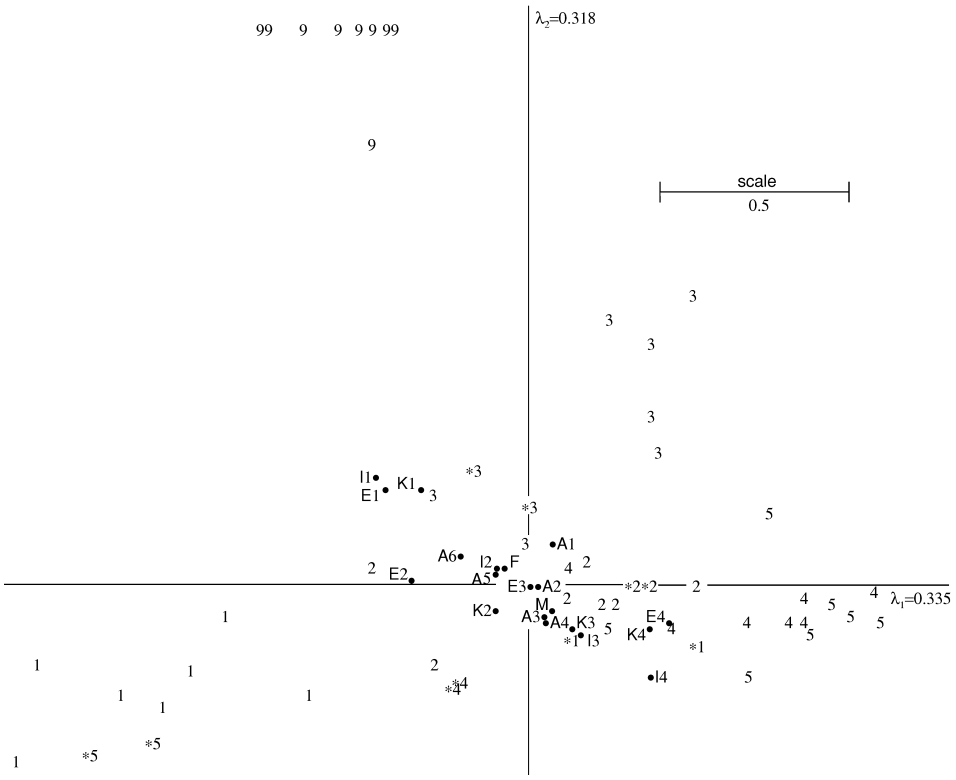

Fig. 2 Multiple correspondence analysis on political efficacy and trust including supplementary variables. (1 = strongly agree, 2 = agree somewhat, 3 = neither agree nor disagree, 4 = disagree somewhat, 5 = strongly disagree, 9 = no opinion.)

"18 to 24"—A1; "25 to 34"—A2; "35 to 44"—A3; "45 to 54"—A4; "55 to 64"—A5; "65 and older"—A6), "education" (four categories: from "grade school or less," E1, to "university degree," E4), "political knowledge" (constructed by counting how many of the 10 Canadian provincial premiers a respondent could name; four categories: from "none or one premier," K1, to "five or more premiers," K4), and "political interest" (four categories: "low interest," I1, to "high interest," I4). These attributes are included in a manner which does not influence the geometric orientation of the axes in the latent space determined by the nine Likert-type items.

By definition, the structure of the responses with respect to the political efficacy and trust items in Fig. 2 is exactly the same as that described for Fig. 1. Turning to the passive variables, one can see that they span both axes. Whereas the ordinality of "educational level," "political interest," and "political knowledge" is mirrored in the two-dimensional map, "age" is not ordinally distributed with respect to either of the first two latent dimensions. According to Fig. 2, the middle-age groups have the highest political knowledge and the highest political interest (note the proximity of the respective categories in the two-dimensional space).

If we use "political interest" to fit a straight line onto the map (Fig. 2), connecting "I1" (low political interest) and "I4" (high political interest) yields the longest line between two "extreme points" of respondents' attributes, with relatively small deviations of "I2" and "I3" to this line. Parallel to this line (and only a little shorter) are the lines of "education" and "political knowledge." Projecting the 54 active categories (9 items with 6 categories

each) onto the new axis determined by "political interest" produces an order ranging from "no opinion" via "strongly agree" and "neither agree nor disagree" to "strongly disagree." The strong associations in the latent space of "political interest," "political knowledge," and "educational level" with the response structure permit one to conclude that the use of "no opinion," of "neither agree nor disagree," and of the degree of "political efficacy and trust in the federal government" are related to these individual characteristics. The higher use of nonsubstantive responses from politically less interested respondents as well as their lower political efficacy and trust confirms previous findings in these respects.

Although the association is weak, males used the nonsubstantive responses less often than females, which also supports previous findings (see, e.g., Francis and Busch 1975). Finally, age is connected with the use of "no opinion" in a nonlinear fashion, which perhaps explains the inconsistent findings in the literature when treating "age" as an ordinal or as a metric variable.

The next question we address is whether the response pattern itself differs by political interest and educational level. To answer this question, we dichotomize the data, using political interest as the control variable. As input for the next analyses we use two subsets of the data with 1479 respondents (high political interest) and 1876 respondents (low political interest) (see Table 1 for their marginals). Since both analyses provide similar distributions of the eigenvalues as in the first analysis, we again examine the two-dimensional maps. The two graphical solutions of multiple correspondence analysis are given in Figs. 3 and 4.

Figure 3 provides the response structure for respondents with high political interest. On the left side of the first dimension are the "strongly agree" responses and on the right are the "strongly disagree" responses, with the remaining categories in between. As expected, the first dimension mirrors a latent continuous variable that can be interpreted as the degree of political efficacy and trust; all 45 Likert-type response alternatives (9 items times 5 categories) are highly associated with this dimension. Furthermore, the response categories for the two items phrased in reversed direction ("h" and "i," again indicated by asterisks) are appropriately located in the opposite direction along the first axis. Thus the responses among those with high political interest appear to be consistent, regardless of the polarity of the questions.

Except for one item, all "no opinion" responses (indicated by a "9"[12]) are clearly related to the second axis and situated very far from the centroid.[13] This means that a small subgroup of politically interested respondents consistently answered with "no opinion." Some of the "neither agree nor disagree" categories (all indicated by "3") are located somewhat in the direction of "no opinion" (especially items "d" and "g"—no distinct label in Fig. 3), but at least they are distant from the "no opinion" responses. From this solution one can conclude that only a few politically interested respondents used the middle categories to mask their nonsubstantive responses; most of them had substantive reasons (see the proximities to the first dimension and the proximities to the other substantive responses). In general, the second dimension mirrors the distinction between substantive (negative part) and nonsubstantive (positive part) responses.

Among the politically less interested respondents the pattern is quite different (Fig. 4). Note especially that the first dimension fails to mirror the ordinal order of the categories of the nine items. Instead, it contrasts a "strongly agree" on the left with a mixture of all

[12] As was the case for Figs. 1 and 2, some of the "9's" would be outside the frame used in Fig. 3; hence they are shifted toward the centroid and lined up on the horizontal axis to provide an easy-to-read display.

[13] The exception is item "f" (many people in the federal government are dishonest; no distinct label in Fig. 3), which has the highest frequency of "no opinion" responses; see Table 1.

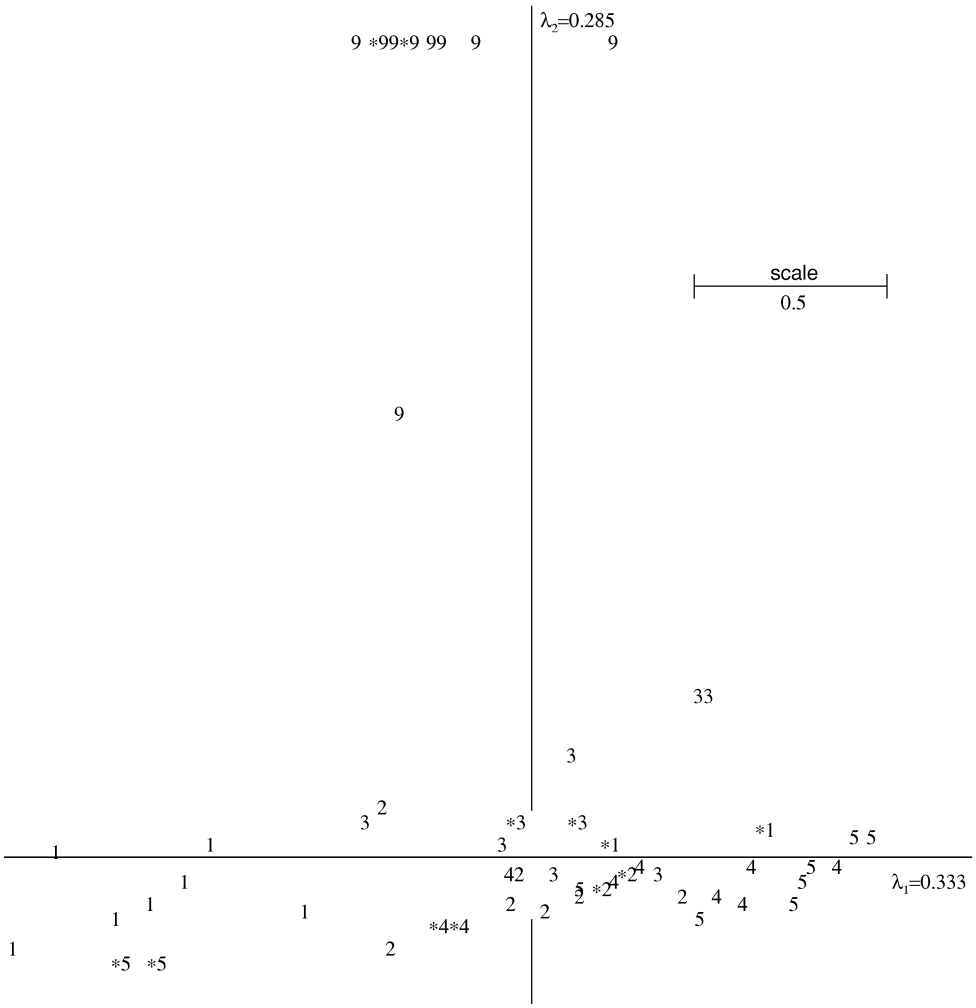

Fig. 3 Multiple correspondence analysis on political efficacy and trust—respondents with high political interest. (1 = strongly agree, 2 = agree somewhat, 3 = neither agree nor disagree, 4 = disagree somewhat, 5 = strongly disagree, 9 = no opinion.)

other categories on the right. Located on the extreme right is the "no opinion" category, as well as the middle category of some of the items (see their projections onto the right part of axis 1). These are strong indications that something is amiss with the measurements. Although the political efficacy and trust items are reasonably valid and reliable instruments when applied to politically interested respondents, it seems that many politically less interested respondents ($N = 1876$, or 55.9% of the total sample) misunderstood some of the statements, especially if they were likely to disagree with them.

Additionally, the "no opinion" responses are neither close to each other nor strongly related just to the second axis, as was the case among the politically interested respondents. The "9's" spread out along the positive parts of the first and the second dimensions. Relatively short distances exist between the "no opinion" and the "neither agree nor disagree" responses, which means that there was some fluctuation in the use of these categories. From

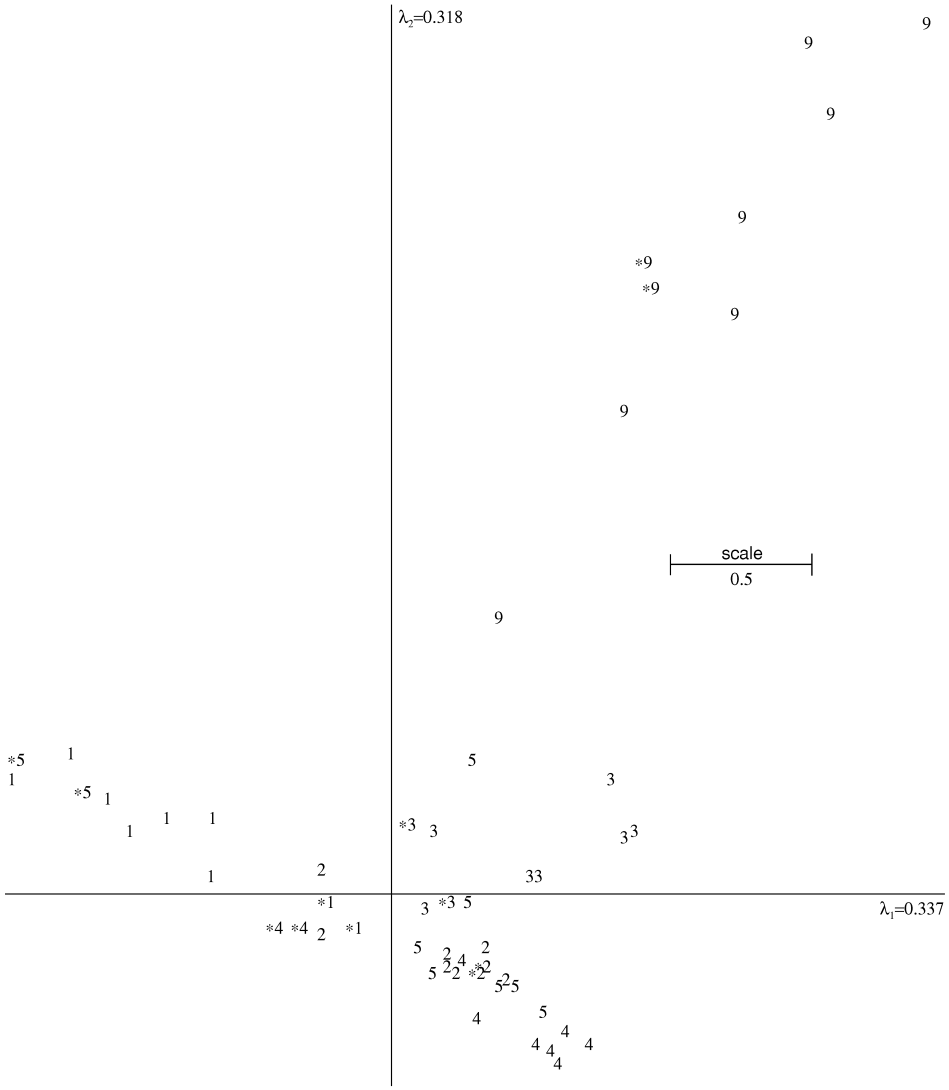

Fig. 4 Multiple correspondence analysis on political efficacy and trust—respondents with low political interest. (1 = strongly agree, 2 = agree somewhat, 3 = neither agree nor disagree, 4 = disagree somewhat, 5 = strongly disagree, 9 = no opinion.)

these findings one can conclude that a sizable number of respondents used the middle categories to hide their nonsubstantive responses (see also their loadings on the positive part on the second dimension).

Finally, the reversed polarity items ("h" and "i"; indicated by asterisks) are clearly not in ordinal order either. Their locations on the first axis are even worse than those of the seven other items: the "strongly agree" responses are very close to the "disagree somewhat" responses. Even more disturbing, "strongly agree" and "strongly disagree" load onto the same part of the first axis, indicating that both are positively associated with this dimension. From this response pattern it can be inferred that a substantial number of the respondents with low political interest did not notice the changed direction of the scale.

For respondents with high political interest we argued that the first dimension reflects the degree of political efficacy and trust in the federal government, with the second axis contrasting substantive and nonsubstantive responses. For respondents with low political interest, neither interpretation holds. Instead, the first axis mirrors the opposition of agreement with the items, with little regard for their content, with nonsubstantive responses (including the "neither–nors"). The positive part of the second axis contains a mixture of critical attitudes toward the federal government (project the "strongly agree" categories onto the second dimension) and nonsubstantive responses; the negative part, a somewhat positive attitude toward the federal government (project the "somewhat disagree" categories onto the second dimension).

To describe the locations of the categories in the two-dimensional space in more detail and to test each item for ordinality, we show them item by item. We do this in Fig. 5, overlapping the plots for respondents with high and low political interest to save space and to facilitate comparison. Solid and dashed lines connect the categories belonging to respondents with high and low political interest, respectively. Note that the distances between the respective variable categories cannot be compared since the axes refer to different data and the eigenvalues of both presentations differ. Although the "no opinion" categories are included in the computations, to save space and to improve the readability of the figure, they are not shown.

Among respondents with high political interest, Fig. 5 confirms well the ordinal orders of the nine items in the first dimension of the latent space. Only two small "errors" (item "e," categories "2" and "3"; item "g," categories "4" and "5") occur and these involve only a few respondents choosing the respective item categories (see the low percentages in Table 1).

On the second axis, the middle categories of some items (especially "b," "d," and "g") point toward "no opinion." If one compares these three items with the others, items "b" and "d" have in common the word "don't," which requires the respondents to assess whether a statement is "not" true; if they could neither agree nor disagree, they probably chose the neutral category, "neither agree nor disagree." The only other item from the list also containing the word "don't" is item "e," which has a small dislocation in the first dimension involving the "neither agree nor disagree" category. Referring to item "g," the expression "waste a lot of the money" is relative, and some respondents might have been uncertain about its meaning and, therefore, chose as a compromise the "neither agree nor disagree" response. This phrasing could also be the reason for the small disorder of the categories "disagree somewhat" and "strongly disagree."

As shown, for politically interested respondents, the first dimension mirrors the degree of political efficacy and trust; for respondents with low political interest this does not hold. For the latter group the only distinction is between "strongly agree" ("strongly disagree" for the items phrased in reversed direction) and all other categories. Comparing the distances between the respective categories within the single items, one could come to the conclusion that "agree somewhat" is most similar to "strongly disagree"—and for items "h" and "i" it seems to be between "strongly agree" and "disagree somewhat."

Looking at items "a" to "g" (except item "f"), it can be seen that the ordinal scales of the manifest variables are not mirrored on the right side of the first dimension; these are the parts where the respondents have to disagree with the statements. Interestingly, items "b," "c," "d," and "e" have a negation in the text ("I don't think," "a person like me can't really," "people like me don't have," "it doesn't matter"). Therefore, to agree with the sentiment, the respondents would have to disagree with the statement as worded, which would require a double negation. From Fig. 5 one can deduce that a substantial number of politically less interested respondents did not understand this principle. If they were favorably inclined

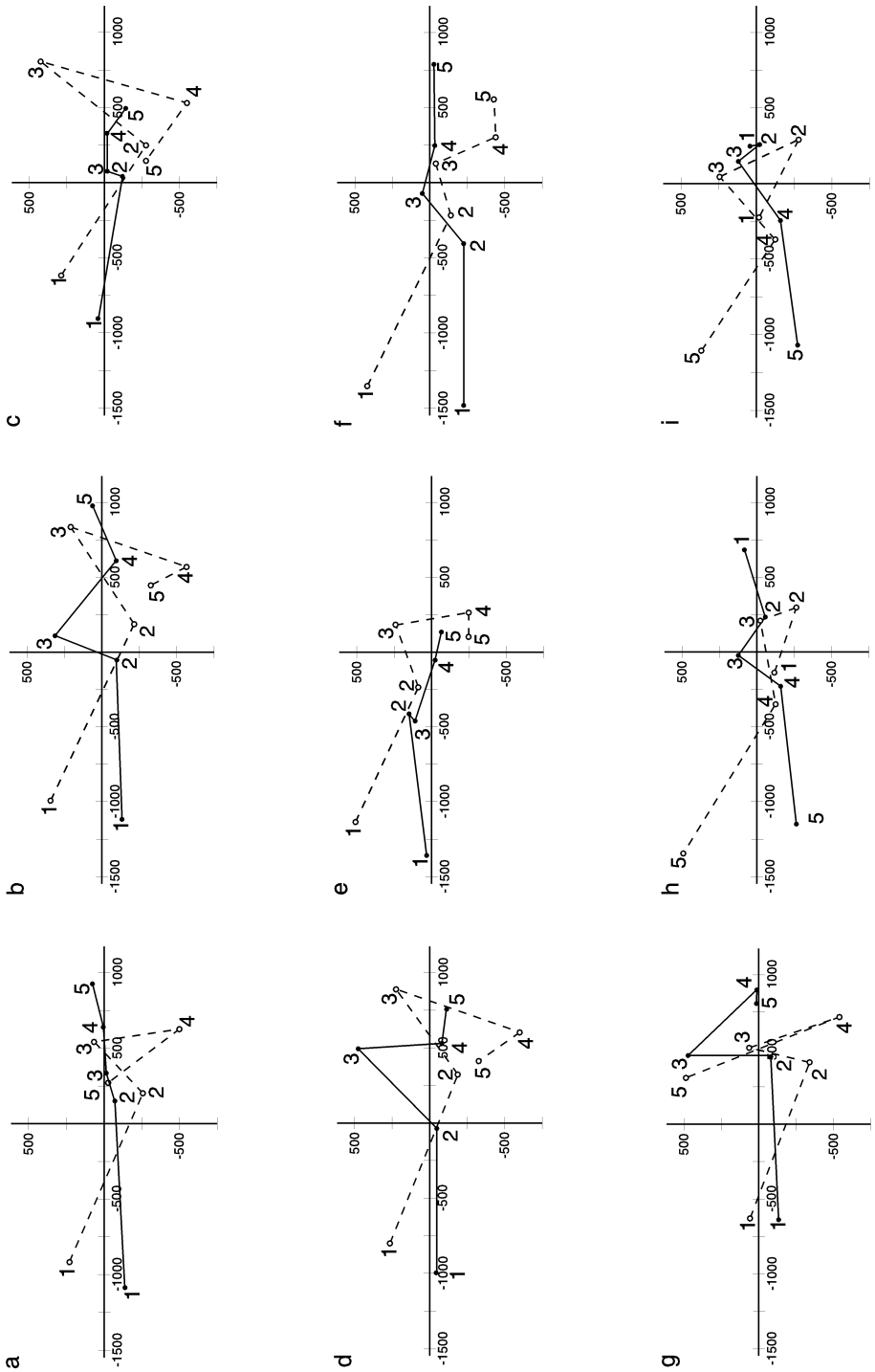

Fig. 5 Multiple correspondence analysis on political efficacy and trust—item by item. (1 = strongly agree, 2 = agree somewhat, 3 = neither agree nor disagree, 4 = disagree somewhat, 5 = strongly disagree.)

toward the federal government, they often gave any response but the "true" one of "disagree somewhat" or "strongly disagree." Furthermore, most of the items include weak expressions such as "soon lose touch," "cares much about," "doesn't matter very much," "seem so complicated," and "a lot of," which can create misunderstandings. In effect, although "strongly disagree" should express the highest trust in the federal government, it reflects less trust than "neither agree nor disagree" and "no opinion" (compare their locations with respect to axis 1 in Fig. 4).

In total, only one item ("f"; many people in the federal government are dishonest) mirrors the ordinality of the manifest variable in the first dimension. Comparing this item with the others, one can see that it is very simply constructed, containing just one thought, no negation, and only eight words.

Referring to the reversed items "h" and "i," one can see that they too have straightforward constructions. Note especially that they contain no negations. Nevertheless, for these two items only the responses from "agree somewhat" to "strongly disagree" are in the expected order, while "strongly agree" is fully misplaced: it is located nearest to "disagree somewhat." Furthermore, since the categories of "strongly agree" are on the same part of the first axis as "strongly disagree," they are both positively associated with the first dimension. Since items "h" and "i" are scaled in the opposite direction and since they are simply constructed (no negations, no weak expressions), the conclusion is that the misplacements of the "strongly agree" categories on the first dimension are caused by a response set. This means that a substantial number of respondents with low political interest failed to pay attention to the direction of the questions and simply responded with "strongly agree."

How do our findings compare with the literature, which concludes that respondents with less political interest or less education have below-average political efficacy and trust? If we consider only Table 1 and Fig. 2, we would confirm these findings: in general, the "strongly agree" responses to the statements are used significantly more often by the politically less interested than by the politically interested. Given that a substantial number of politically less interested respondents could not comprehend the items and did not pay attention to the direction of the statements, the question, however, arises, What do they mean when consistently responding with "strongly agree"? For the reversed items we could show that some of them failed to pay attention to the direction of the question, but what about the other seven items? Were they aware of the direction?

We also showed that the difficulties in responding to the items increase especially with double negation and the use of weak expressions such as "soon lose" and "seem so complicated." But could it be that politically less interested respondents are consistently using the "strongly agree" response as a socially desirable answer to avoid a nonsubstantive answer or to hide that they did not understand the question? In other words, could the higher amount of political distrust assigned to the less educated or politically less interested be nothing more than a measurement artifact produced by asking complicated questions? If this possibility has merit, it would follow that the simpler the question wording (straightforward sentences, no negations and no weak expressions), the less the differences in political efficacy and trust between politically less and more interested respondents.

Looking at the "strongly agree" column in Table 1, the differences between politically more and politically less interested respondents indeed vary with the difficulty of the statements. Such differences are minor in relatively simple statements such as item "f" (many people in the federal government are dishonest; 11.6% versus 9.1%) and item "g" (people in the federal government waste a lot of the money we pay in taxes; 46.3% versus 46.5%). For relatively simply constructed items phrased in the opposite direction, the political efficacy and trust of the respondents with less political interest are even above-average

(compare the "strongly disagree" responses): item "h" (most of the time we can trust people in the federal government to do what is right; 8.8% versus 10.8%) and item "i" (most of the people running the federal government are smart people who usually know what they are doing; 7.4% versus 9.2%).[14] In contrast, the largest differences are found in the complicated questions. The biggest one (with 39.1% versus 20.6%) is on the most complicated question—item "c," which includes a negation, the weak expressions "sometimes," "seem so complicated," "really understand what's going on," and distinctions between "politics" and "government." This interpretation would also explain the reported positive association between the "strongly agree" answers and the nonsubstantive responses along the second axis (as shown in Fig. 4); in a substantial number of cases "strongly agree" would also be used to hide a nonsubstantive response.

In the analyses presented here, we used political interest as a control variable. The choice of this control variable was based mainly on its high associations with political efficacy and trust in previous research. Using educational level instead provides a similar solution: the better-educated have a clear response pattern in which the ordinality of the items can be mirrored by the first dimension; for the less educated respondents this solution does not hold.

4 Conclusion

The concern of this paper was to exemplify how multiple correspondence analysis can be used to expose measurement effects that might masquerade as structural relationships. Approaching the measurement of political efficacy and trust from a vantage point that differs from that used in previous analyses in certain respects, the main differences are as follows.

1. We used a procedure which assesses rather than assumes ordinality of the items.
2. We used a more complete set of items in contrast to the subset of items (often four) used, providing a better base from which to detect response patterns.
3. The items we used include two with reversed polarity, which permitted us to examine and detect response sets and agreement bias.
4. We utilized graphical displays which permit an interpretation of the meaning of response categories based on their locations in a latent space.
5. We used a substantively important variable (political interest) as a "control variable." Doing this made it possible to explore whether theoretical relationships (political interest and education with political efficacy and trust) might be due to methodological shortcomings.

The results of our analyses reveal the existence of several methodological problems. The first one concerns the assumed ordinality of the political efficacy and trust items measured on a 5-point scale. In the 1984 Canadian National Election Study, the ordinality of the item categories along the first dimension can be confirmed only for the politically interested. For respondents with low political interest, we could not confirm ordinality. The same holds if we subdivide the sample on the basis of education.

The second methodological problem is that of response sets. The fact that two of the items were asked in reversed polarity permitted us to show the existence of a response set among the politically less interested respondents. The response structure in this subgroup reveals

[14] Please note that the values for the respondents with low political interest are also affected by response sets.

that a substantial number of them were oblivious to the reversed polarity. In contrast, politically interested respondents were sensitive to the direction of the questions. Furthermore, the more complicated a question, the more likely were the respondents to answer simply with "strongly agree." Whether an item was too complicated depends on the educational level of the respondents—and in the given case, especially on their political interest.

The last methodological problem is that of the meaning of the middle categories in 5-point Likert-type scales. This is also part of a larger discussion about which item categories (or which responses) should be treated as nonsubstantive and which as substantive. This is, for example, the case with "neither agree nor disagree" in 5-point scales. In the given example we could show that the middle categories were used both to mask a nonsubstantive response (mainly among the politically less interested respondents) and to give a substantive response (mainly among the politically interested respondents). The effect on the response structure caused by these methodological problems combined to cast into doubt the frequently reported relationships of education and political interest with political efficacy and trust.

Multiple correspondence analysis can be understood as principal components analysis with categorical data. In survey research more or less all information is categorical; de Leeuw (1998, p. 4) pointed out that "*All Data Are Categorical*," although perhaps some data are more categorical than others. But as shown, here data which are assumed to be more than categorical, say ordinal, might not be; applying techniques which assume ordinal or even metric data to these variables might lead to wrong conclusions. There are of course alternative statistical procedures for analyzing categorical data. Some of them, such as loglinear modelling and latent class analysis could be employed to explore the issues raised in this paper (for the similarities of these techniques, see for example van der Heijden et al. 1989, 1994). The advantage of (multiple) correspondence analysis lies in its capability of permitting a theoretically unlimited number of variables to be included simultaneously in the analysis. The graphical displays produced are also invaluable interpretive aids, permitting one to grasp the Gestalt of the response structures.

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