## Research Article

# When Do Men Represent Women's Interests in Parliament? How the Presence of Women in Parliament Affects the Legislative Behavior of Male Politicians

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## Online Appendix

**A1 Share and Number of Female MPs Across Parties (1998-2013)**

Appendix A1 presents descriptive information on the share and number of female MPs across parties in the German Bundestag over time (1998-2013).

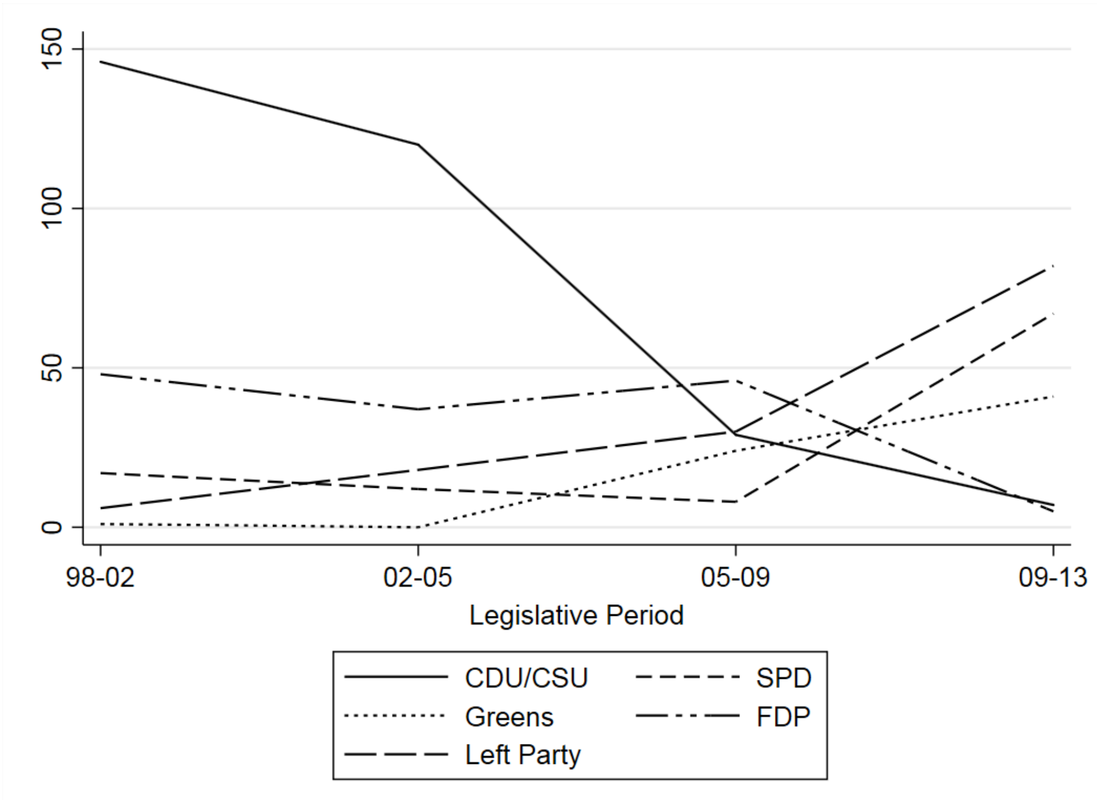
Table A1: Share and Number of Female MPs Across Parties (1998-2013)

| Legislative Period | CDU/CSU | SPD | FDP | Greens | Left |
|---|---|---|---|---|---|
| 14 (1998-2002) | 18.2<br>(47) | 36.0<br>(110) | 24.4<br>(11) | 58.0<br>(29) | 59.0<br>(23) |
| 15 (2002-2005) | 23.4<br>(60) | 38.8<br>(100) | 23.6<br>(13) | 59.7<br>(34) | -<br>- |
| 16 (2005-2009) | 19.8<br>(47) | 36.4<br>(83) | 23.8<br>(15) | 55.4<br>(31) | 47.3<br>(26) |
| 17 (2009-2013) | 20.0<br>(49) | 39.6<br>(61) | 24.0<br>(24) | 52.0<br>(39) | 53.9<br>(42) |
| *Average* | 20.4<br>(51) | 36.7<br>(93) | 23.3<br>(17) | 56.5<br>(34) | 53.4<br>(30) |

*Note*: Absolute number of women in the PPG in parentheses.

**A2 Number of Women-Specific Parliamentary Questions Tabled by Male MPs (1998-2013)**

Figure A1: Number of Women-Specific Parliamentary Questions Tabled by Male MPs Across Parties (1998-2013)



**A3 Description and Validation of the Automated Coding of Parliamentary Questions**

Appendix A3 provides a detailed description of the automated coding procedure of women-specific parliamentary questions (PQs).

The analysis uses a combination of two different methods of automated content classification: (1) A supervised machine learning algorithm (Naïve Bayes classifier) and (2) a dictionary-based approach.

Prior to the analysis, the PQ text corpus had to be transformed into a sparse document-term-matrix (DTM) which required extensive pre-processing of the original PQs (Welbers et al. 2017; Grimmer and Stewart 2013): All the documents were tokenized to split each question into single words and then normalized into a more uniform form. This includes transforming all features (words) to lowercase and reducing them to their stem form (e.g. the words *family* and *families* are reduced to *famil*). Moreover, stop words with no semantic meaning (e.g. *the* or *a*) as well as very rare (appearance in less than 10 documents) and very frequent (appearance in more than 20% of the documents) features were deleted from the corpus to reduce the size of the vocabulary and to improve the efficiency and accuracy of the subsequent classification (Lucas et al. 2015; Welbers et al. 2017).

The basic idea of supervised learning models is quite simple: A subset of documents is classified into specific categories by human coders. An algorithm then uses this training set to learn specific patterns and attributes determining the classification of the documents into one of the categories. If the training set is sufficiently large, the algorithm can then be used to classify the rest of the corpus into the pre-determined categories. In order to create the training set for the present analysis, all the questions from the 16th and 17th Bundestag (2005-2013) were hand-coded by the author to identify whether or not they dealt with a women-specific topic (the definition of women's interests can be found in the main paper).

All the training set's questions were used to train a Naïve Bayes classifier the relationship between document features and the classification of questions as women-specific. The classifier uses Bayes' rule[1] and a multinomial distribution of features within the documents to infer the probability that, based on the word profile of the document, a specific question belongs to the category of women-specific questions (Grimmer and Stewart 2013). The trained classifier was then used to classify all PQs which were tabled during the Bundestag's 14th and 15th legislative periods.

Since this supervised model is intended to automate the hand coding of questions, it was necessary to carefully validate the algorithm's performance after the classifier had been trained. At first, it is advisable to look at the most important features (words) which determine the classification of questions into the women's interest category. These are: frau* (*women**), schwanger* (*pregnant**), elternzeit (*parental leave*), kinderbetreuung (*childcare*), and alleinerziehend (*single mother*). Moreover, results of a *V*-fold cross-validation with 20 subgroups indicate that the classifier achieved an averaged *balanced accuracy* of 0.78, which means that 78% of all questions have been correctly

[1] $P(womenspecific \mid feature) = \frac{P(feature|womenspecific) * P(womenspecific)}{P(feauture)}$

classified as either women-specific or non-women-specific. When only the questions that referred to a women's issue were considered, the classifier was able to identify 70% of the questions that had been coded as women-specific by the human coder (*recall*). However, the classifier's *precision* (number of questions that the classifier correctly labelled as women-specific divided by the total number of questions that the classifier coded as women-specific) was only 17%, which means that the Naïve Bayes algorithm tended to produce many false-positives.

Even though the classifier had reached a comparatively high level of accuracy and recall (see Grimmer and Stewart 2013), a dictionary-based approach was applied independently of the supervised machine learning algorithm, to further enhance the classification's validity and to identify obviously women-specific questions that the Naïve Bayes classifier had erroneously classified as non-women-specific. In general, dictionary-based approaches use the frequency of keywords to classify texts into specific categories (Grimmer and Stewart 2013). Thus, a dictionary of women-specific keywords was created, based on the hand-coded questions from the 16th and 17th Bundestag. All the questions were then searched for these keywords and classified as women-specific if they contain at least one of them. A list of all the keywords can be found below.

Of the 28748 PQs that were automatically coded, both methods identified 3648 questions as referring to a women-specific issue. Since both methods tend to have high recall-levels, but only low precision (i.e. they produce a high number of false-positives), all questions that had been identified as women-specific by either the Naïve Bayes classifier or the dictionary-approach, were reviewed manually in the last step of the classification to determine whether it really dealt with a women's issue. This reduced the number of women-specific questions to 774. 413 of the 774 women-specific questions were identified by both methods. 34 questions were only identified by the supervised learning algorithm whereas 327 were only coded as women-specific by the dictionary-based approach. Thus, the combination of both methods and the subsequent human control seem to be an appropriate way to enhance the validity and the accuracy of the automated coding of PQs.

**A4 Keywords Dictionary Approach**

A3 provides a full list of all keywords that have been used in the dictionary-approach to identify women-specific PQs. All words have been used in singular and plural (if applicable). Words with a * have been truncated in the search. Exemplary results for truncated searches in brackets. Please see below for English translations.

Frau* (Frauenanteil, Frauenquote, Frauenrechte, Frauenspezifisch, Frauenhandel, Frauenhaus, Frauenarzt, Frauenhaftanstalt, Frauengefängnis, Frauenhändler, Ombudsfrau, Ehefrau), weiblich*, Geschlecht* (Geschlechtsspezifisch), Gender*, Gender Mainstreaming, Mädchen* (Mädchenhandel, Mädchenhändler), Schwanger* (Schwangerschaft, Schwangerschaftsabbruch, Schwangerenvorsorge), Geburt* (Geburtshilfe), Baby* (Babyklappe), Embryo, Entbindung, Kontrazeptiva, Verhütung, Pille, Notfallkontrazeptiva, Abtreibung, Reproduktionsmedizin, Ungeboren, Künstliche Befruchtung, Präimplantationsdiagnostik, Kinder* (Kinderbetreuung, Kindertagesstätte, Kindergarten, Kinderkrippe, Kindererziehung, Kinderfreibetrag), Krippe, Kita, Ganztagesschule, Ganztagsbetreuung, Erziehung* (Erziehungsgeld, Erziehungsurlaub), Mutterschutz, Stillzeit, Tagesmutter, Mutter*, Vater* (Vaterschaftstest, Vaterschaft), Eltern* (Elterngeld, Elternzeit), Alleinerziehend, Familie* (Familiensplitting, Familienförderung), Ehe* (Ehegattensplitting), Gleichstellung* (Gleichstellungsbeauftragte, Gleichstellungspolitik), Feminismus, Feministin, Feministisch, Gleichberechtigung, Gleichbehandlung, Chancengleichheit, Ungleichheiten, Equal Pay, Diskriminierung, diskriminierend, Vergewaltigung, Vergewaltigt, Belästigung, Prostitution, Prostituierte, Genitalverstümmelung, Beschneidung, Zwangsheirat, Zwangshochzeit, Zwangsverheiratung, Sex* (Sexuell, Sexualstraftäter, Sextourismus), Häusliche Gewalt, Ehrenmord, Menschenhandel, Scheidung, Geschieden, Unterhalt, Witwe, Hinterbliebenenrente, Betreuung*, Lesbe, Lesbisch, Damen, Kopftuch, Verschleierung, Gynäkologe, Gynäkologie, Brustkrebs, Mammographie, Gebärmutter*, Eierstock*, Unfruchtbar, Unfruchtbarkeit, Klimakterisch, Klimakterium, Wechseljahre, Menopause, Menstruation, Östrogen, Brustimplantat, Silikonimplantat, Hebamme, Sekretärin, Krankenschwester, Soldatin, Professorin, Politikerin, Podologin, Arzthelferin, Altenpflege, Aupair, Au-pair, Pflege, Haushaltskraft

English Translation (Without Examples of Truncated Searches)

Woman, women-specific, female, gender, gender mainstreaming, women's rights, girl, pregnancy, abortion, prenatal care, birth, embryo, child, childcare, contraceptive, contraception, abortion, reproductive medicine, artificial insemination, preimplantation diagnostics, kindergarten, all-day school, full-day care, parent, parental leave, maternity leave, breast-feeding, childminder, nanny, mother, father, paternity, wife, single mother, family, marriage, equality, quota, feminism, feminist, equal rights, equal treatment, equal opportunities, inequality, equal pay, pay gap, discrimination, rape, harassment, prostitution, prostitute, genital mutilation, forced marriage, sex, sexual, domestic violence, honor killing, human trafficking, divorce, divorced, alimony, child support, widow, care, elderly care, lesbian, lady, headscarf, veil, gynecologist, gynecology, breast cancer, mammography, uterus, ovary, infertile, infertility, menopause, climacteric, menstruation, estrogen, breast implant, silicone implant, midwife, secretary, nurse, au pair, nursing

## A5 Descriptive Statistics

This appendix shows descriptive statistics for all variables used in the analysis.

Table A5: Descriptive Statistics

| | Full Data Set | | | | | Male MPs only | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variables | N | Mean | Stand. Dev. | Min | Max | N | Mean | Stand. Dev. | Min | Max |
| Share women-specific quest. | 2619 | 0.02 | 0.07 | 0 | 1 | 1773 | 0.01 | 0.06 | 0 | 1 |
| Women-specific quest.>0 | 2619 | 0.18 | 0.38 | 0 | 1 | 1773 | 0.14 | 0.35 | 0 | 1 |
| Share of women PPG | 2619 | 32.3 | 12.4 | 18.2 | 59.7 | 1773 | 30.0 | 11.4 | 18.2 | 59.7 |
| Member women's committee | 2619 | 0.05 | 0.21 | 0 | 1 | 1773 | 0.02 | 0.15 | 0 | 1 |
| Leadership position | 2619 | 0.24 | 0.43 | 0 | 1 | 1773 | 0.23 | 0.42 | 0 | 1 |
| Duration MP (years) | 2619 | 6.89 | 6.70 | 0 | 37 | 1773 | 7.43 | 7.44 | 0 | 37 |
| Age | 2619 | 49.47 | 9.41 | 19 | 74 | 1773 | 50.11 | 9.60 | 22 | 74 |
| District mandate | 2619 | 0.47 | 0.50 | 0 | 1 | 1773 | 0.53 | 0.50 | 0 | 1 |
| No. of submitted questions | 2619 | 26.81 | 45.45 | 0 | 332 | 1773 | 25.25 | 43.21 | 0 | 332 |
| SPD | 2619 | 0.36 | 0.48 | 0 | 1 | 1773 | 0.33 | 0.47 | 0 | 1 |
| CDU/CSU | 2619 | 0.38 | 0.49 | 0 | 1 | 1773 | 0.45 | 0.50 | 0 | 1 |
| FDP | 2619 | 0.10 | 0.30 | 0 | 1 | 1773 | 0.11 | 0.32 | 0 | 1 |
| Greens | 2619 | 0.09 | 0.29 | 0 | 1 | 1773 | 0.06 | 0.24 | 0 | 1 |
| Left | 2619 | 0.07 | 0.25 | 0 | 1 | 1773 | 0.05 | 0.21 | 0 | 1 |
| Female population (share) | 2619 | 0.51 | 0.007 | 0.49 | 0.54 | 1773 | 0.51 | 0.007 | 0.49 | 0.54 |
| East Germany | 2619 | 0.21 | 0.41 | 0 | 1 | 1773 | 0.20 | 0.40 | 0 | 1 |

*Note*: Data for the years 1998-2013.

**A6 Test for a Curvilinear Relationship Between Share of Women and Substantive Representation of Women by Male MPs**

This appendix tests for a curvilinear relationship between the share of women and men's parliamentary behavior (spill-over effect at low-levels of women's representation, backlash-effect if the proportion of women is high). The results are statistically insignificant.

Table A6: Quadratic Regression: Substantive Representation of Women by Male MPs, 1998-2013 Log-Odds

| Variables | General decision (Logit-Regression) | Intensity of Substantive Representation (Beta Regression) |
|---|---|---|
| Share of women in PPG | 0.14 (0.142) | -0.07 (0.086) |
| Share of women in PPG (squared) | -0.001 (0.002) | 0.0001 (0.001) |
| Member women's committee | 1.04* (0.427) | 0.60* (0.290) |
| Leadership position | -0.05 (0.210) | 0.27 (0.181) |
| Duration MP | 0.01 (0.015) | -0.001 (0.009) |
| Age | -0.02* (0.010) | -0.002 (0.005) |
| District mandate | -0.42* (0.191) | -0.03 (0.105) |
| No. of submitted questions (in total) | 0.03*** (0.003) | -0.01*** (0.002) |
| CDU/CSU | 2.22 (1.162) | -1.64* (0.666) |
| FDP | 1.93* (0.909) | -1.24* (0.524) |
| Greens | -1.65 (1.107) | 0.73* (0.365) |
| Left | -0.64 (0.988) | 0.78* (0.335) |
| East Germany | 0.49* (0.200) | 0.12 (0.100) |
| Time fixed effects | ✓ | ✓ |
| Constant | -5.66 (3.302) | 0.66 (1.822) |
| N | 1773 | 253 |
| Log-Pseudolikelihood | -542.10 | 502.78 |
| Chi² | 381.53*** | 124.57*** |

*Notes*: Hurdle Regression Model. DV Model 1: Dummy variable coded 1 if share of women-specific questions > 0. DV Model 2: Share of women-specific questions. Coefficients: Log-Odds. Standard errors (in parentheses) are clustered by MP. Reference category for parties: SPD. Significance Levels: * p<.05; ** p<.01; ***p<.001. Source: Own calculations.

## A7 Effect of Anticipated Share of Female MPs After the Next Election

Appendix A5 includes the proportion of female MPs in the subsequent legislative term (t+1) as its main independent variable to test whether male MPs anticipate an increase in the number of female MPs after the next election. The results are statistically insignificant.

Table A7: Substantive Representation of Women by Male MPs, 1998-2013. Independent Variable: Share of Women in PPG at t+1 (Subsequent Legislative Term)

| Variables | General decision (Logit-Regression) | Intensity of Substantive Representation (Beta Regression) |
|---|---|---|
| Share of women in PPG at t+1 | 0.01 (0.022) | -0.01 (0.008) |
| Member women's committee | 0.82 (0.573) | 0.35 (0.276) |
| Leadership position | 0.02 (0.237) | 0.26 (0.198) |
| Duration MP | -0.01 (0.018) | -0.01 (0.011) |
| Age | -0.01 (0.012) | -0.001 (0.005) |
| District mandate | 0.01 (0.233) | -0.16 (0.124) |
| No. of submitted questions (in total) | 0.03*** (0.004) | -0.01*** (0.002) |
| CDU/CSU | 1.26** (0.481) | -1.17*** (0.251) |
| FDP | 1.50** (0.533) | -1.04*** (0.218) |
| Greens | 0.18 (0.757) | -0.55 (0.321) |
| Left | 0.33 (1.108) | -0.10 (0.453) |
| East Germany | 0.42 (0.229) | -0.02 (0.100) |
| Time fixed effects | ✓ | ✓ |
| Constant | -3.12** (1.118) | -0.67 (0.467) |
| N | 1336 | 196 |
| Log-Pseudolikelihood | -398.67 | 397.36 |
| Chi² | 327.27*** | 150.68*** |

*Notes*: Hurdle Regression Model. DV Model 1: Dummy variable coded 1 if share of women-specific questions > 0. DV Model 2: Share of women-specific questions. Coefficients: Log-Odds. Standard errors (in parentheses) are clustered by MP. Reference category for parties: SPD. Significance Levels: * p<.05; ** p<.01; ***p<.001. Source: Own calculations.

**References**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Lucas, C., R. Nielsen, M. Roberts, B. Stewart, A. Storer and D. Tingley (2015). Computer-Assisted Text Analysis for Comparative Politics. *Political Analysis* 23(2): 254–277.

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