Appendix of Advocacy campaigns and gender bias in media coverage of elections

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A. Classifier

To achieve dependable classification of data extracted from newspaper articles and Twitter in both German and French, an ensemble approach was employed which was trained in a previous work (Gilardi et al., 2022). The ensemble model aggregates the probabilities of the individual classification topics and selects the class with the highest probability as the final classification. To train the models, a comprehensive hyper-parameter space was explored using random grid search and regularization techniques, coupled with early stopping techniques, to optimize all classification algorithms.

The average F1 scores for the top-performing deep learning models typically range between 0.50 to 0.89, depending on the classifier and topic. Despite this strong performance, the best Gradient Boosting models surpass these scores, with F1 scores ranging from 0.60 to 0.89. Given the promising performance of individual models, it may seem unnecessary to incorporate an ensemble model. However, the variability in error rates across different classification algorithms and classes highlights the need for ensemble methods to ensure robust and accurate classification. Although the deep learning models and Gradient Boosting models exhibit favorable overall F1 scores of 0.74, their performance can be significantly enhanced by leveraging an ensemble approach.

The incorporation of multiple models can enhance classification performance for topics that exhibit sub-optimal results within a singular algorithm. This is demonstrated through the improved F1 score of the "Law and order" topic within the ensemble model, reaching 0.77, compared to only 0.70 in the top two Deep Learning models and 0.75 in the Gradient Boosting model. Furthermore, the classification of French texts achieved F1 scores ranging from 0.74 to 0.93 for Deep Learning models, and from 0.77 to 0.95 for Gradient Boosting models, indicating the benefit of utilizing multiple models to improve classification accuracy for varying topics and languages.

Topic	German			French		
	Precision	Recall	F1	Precision	Recall	F1
Agriculture	0.91	0.80	0.85	0.95	0.85	0.89
Public Health	0.90	0.87	0.88	0.96	0.89	0.92
Education & Culture	0.87	0.80	0.83	0.86	0.86	0.86
Environment & Energy	0.84	0.81	0.83	0.86	0.88	0.87
Public Services & Infrastructure	0.83	0.82	0.82	0.91	0.88	0.89
Economy	0.83	0.83	0.83	0.91	0.88	0.89
Immigration & Asylum	0.81	0.77	0.79	0.85	0.80	0.83
Finance & Taxes	0.81	0.77	0.79	0.85	0.80	0.83
Political System	0.81	0.70	0.75	0.86	0.82	0.84
Social Security & Welfare State	0.79	0.80	0.80	0.87	0.84	0.85
Gender Issues & Discrimination	0.78	0.84	0.81	0.83	0.91	0.87
Law & Order	0.77	0.77	0.77	0.96	0.92	0.94
International Relations	0.75	0.73	0.74	0.82	0.77	0.79
Other Problems	0.75	0.74	0.74	0.87	0.80	0.83
EU & Europe	0.73	0.79	0.76	0.77	0.85	0.81
Labour Market	0.71	0.77	0.74	0.91	0.85	0.88
Regions & National Cohesion	0.71	0.71	0.71	0.83	0.78	0.81
Not Classified	0.49	0.67	0.57	0.76	0.82	0.79
All Topics	0.78	0.77	0.78	0.87	0.85	0.86

Table A.1: *Classification Performance for Newspaper Articles*

Through the incorporation of diverse algorithms within the Ensemble method, we are able to mitigate error rates for topics that exhibit sub-optimal performance with a singular algorithm, resulting in an F1 score of 0.71 or greater for all political topics in German and 0.81 or greater for French political topics (Table A.1). The precision, recall, and F1 score consistently exceed 0.79, indicating highly satisfactory classification performance. Importantly, the absence of systematic classification issues across topics attests to the efficacy of the Ensemble approach in promoting accurate and robust classification.

B. Named entity recognition

In this section, we provide a comprehensive explanation of the Named Entity Recognition (NER) process employed to identify mentions of candidates in the Swiss general elections of 2015 and 2019, bridging insights from political science and computational social science. NER is an annotation technique that extracts user-specified entities from text data. We deployed NER primarily to annotate the candidates mentioned in newspaper articles, allowing us to discern which candidates were referenced in specific articles.

NER typically employs complex pre-trained machine learning algorithms, such as spaCy or NLTK, which syntactically and lexically analyze text data to identify various entity types, such as geographical entities or individuals. When the nature of entities to be identified in the text is not predetermined, applying such algorithms becomes a sensible approach. However, machine learning-based entity recognition can sometimes result in misclassifications, which simpler methods can help mitigate (Goyal et al., 2018).

In our case, we possessed curated lists of individuals—candidates—whom we aimed to identify within the text. Therefore, we opted for a conservative three-step approach. In the first step, we encoded the names of all candidates into regular expressions, treating second names and multiple surnames as optional elements to search for both full names and abbreviated alternatives. In the second step, we extracted four sentences before and after the mention of a name and collected these excerpts in a corpus. In the third step, we verified whether the political party of the mentioned candidate was also present within these excerpts. If not, we could not rule out the possibility that the mention pertained to another individual with the same name, rather than the candidate. This final step served as a preventive measure against false positives, which are instances of incorrectly matched text excerpts.

The combined methodology of candidate list compilation, Bash search, contextual validation, and regular expression encoding facilitated precise candidate mention extraction while reducing the likelihood of false positives. This methodological approach ensured the accuracy and reliability of our analysis concerning the Swiss general elections in 2015 and 2019.

C. Chronology of the election year

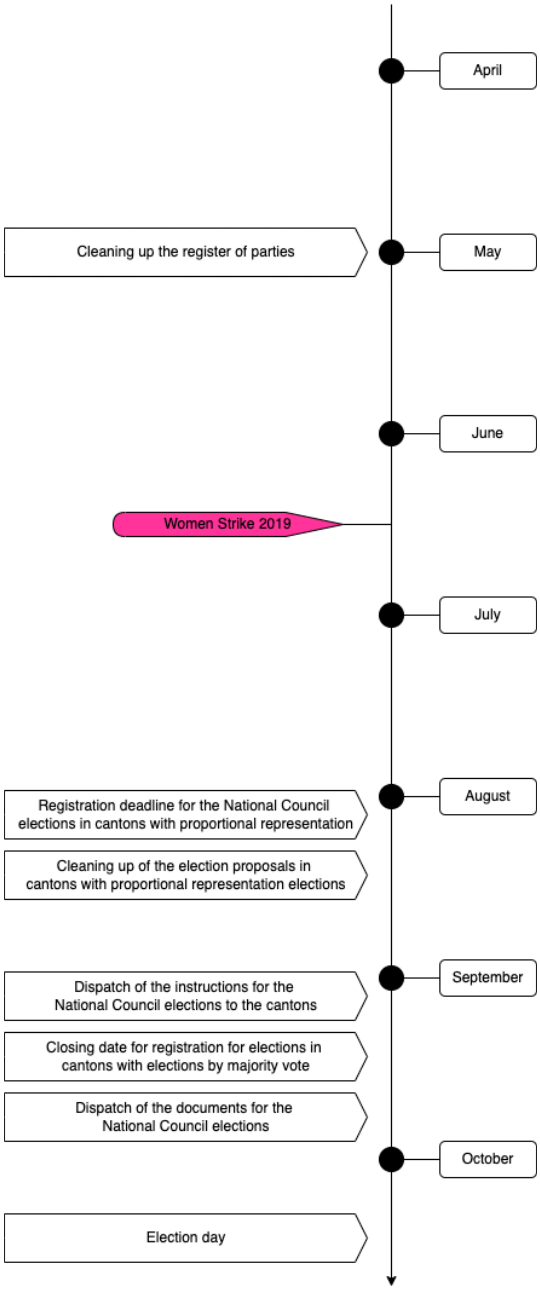

Figure A.1: Simple flowchart of the election year chronology

D. Additional Figures and Tables

	2015	2019
Share of Women on Lists	34.5 %	40.0 %
Share of Women in Data	34.4 %	40.2 %
Number of Candidates	3,788	4,652
Number of Mentions	132,456	242,722
Number of Articles with one or more Mentions	47,796	73,815

Table A.2: *Descriptive summary of the corpus*

Topic	Number of Articles		Percent Share	
	2015	2019	2015	2019
Political System	68,755	111,461	29.21	30.3
Environment	14,954	33,143	6.35	9.01
Public Services	24,392	33,044	10.36	8.98
Economy	17,906	24,630	7.61	6.7
Education & Culture	19,527	21,565	8.3	5.86
Social Security & Welfare State	10,874	18,358	4.62	4.99
International Relations	8,605	18,139	3.66	4.93
Law Order	9,297	17,827	3.95	4.85
Europe & EU	4,434	17,247	1.88	4.69
Public Health	7,622	16,150	3.24	4.39
Finances & Taxes	10,646	11,674	4.52	3.17
Regions & National Cohesion	11,746	10,393	4.99	2.83
Agriculture	6,067	9,374	2.58	2.55
Gender	1,405	8,105	0.6	2.2
Immigration	12,681	7,244	5.39	1.97
Other Political Topics	3,836	6,200	1.63	1.69
Labour Market	2,620	3,287	1.11	0.89

Table A.3: *Topic Distribution from 2015 and 2019 excluding non political articles*

Year	Name	Running	Elected
2015	Pascale Bruderer	Yes	Yes
2015	Christine Egerzeigi-Obrist	Yes	Yes
2015	Anita Fetz	Yes	Yes
2015	Liliane Maury Pasquier	Yes	Yes
2015	Anne Seydoux-Christe	Yes	Yes
2015	Géralding Savary	Yes	Yes
2015	Verena Diener	No	-
2019	Pascale Bruderer	No	-
2019	Anita Fetz	No	-
2019	Liliane Maury Pasquier	No	-
2019	Anne Seydoux-Christe	No	-
2019	Karin Keller-Sutter	No	-
2019	Brigitte Häberli-Koller	Yes	Yes
2019	Géralding Savary	No	-

Table A.4: In 2015, six out of of seven female incumbents in the Council of State ran for re-election. In 2019, one out of seven female incumbents in the Council of State ran for re-election.

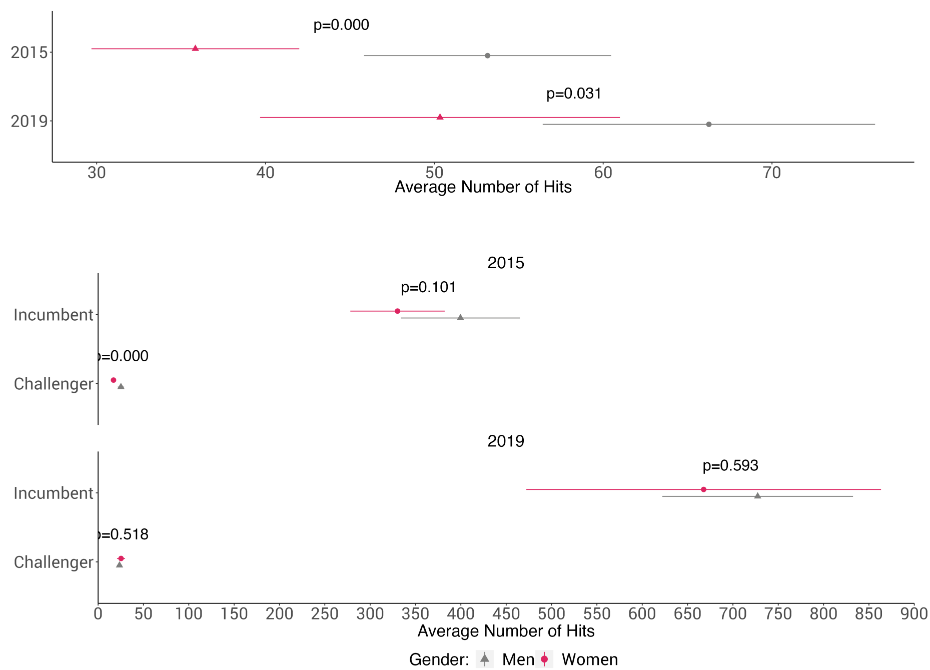

Figure A.2: Average mentions of female and male candidates, dependent on incumbency (including party leaders).

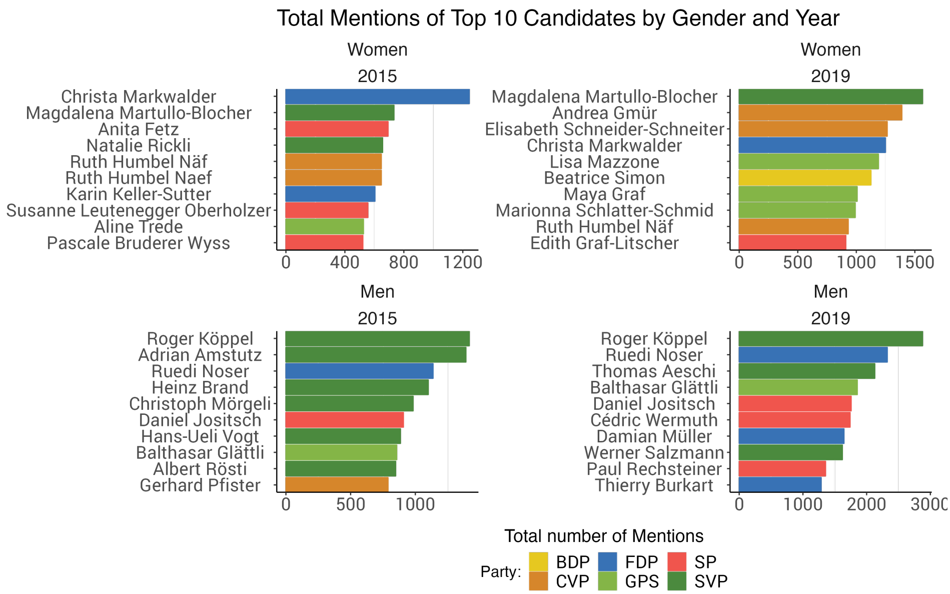

Figure A.3: Presents a comprehensive visual analysis of candidate media mentions, segregated by gender and election years, 2015 and 2019. Each subplot provides a detailed representation of the most-mentioned male and female candidates

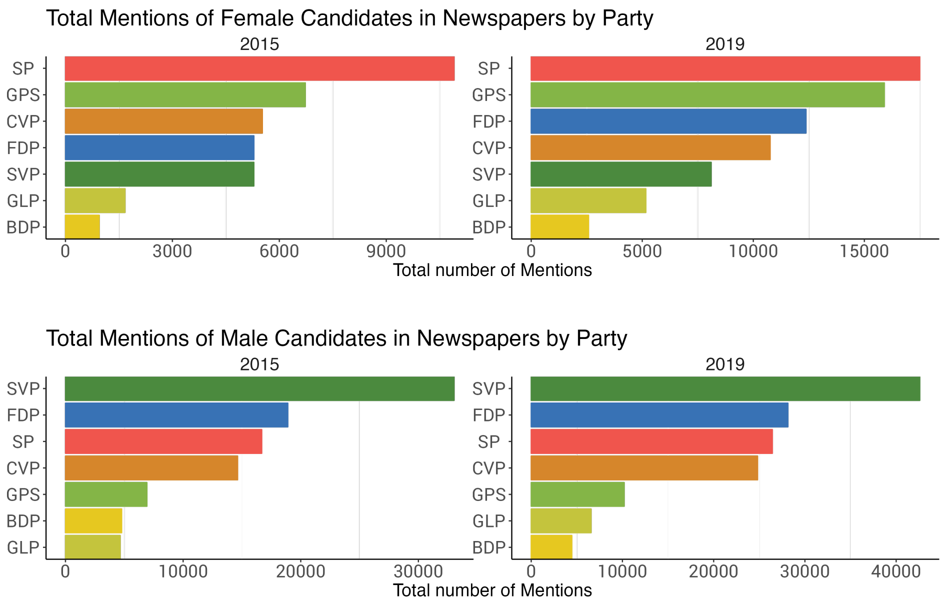

Figure A.4: Illustrates the total media mentions of female and male candidates affiliated with various political parties during the 2015 and 2019 elections. The data is faceted by gender and election year, to offer a detailed comparative analysis. This visualization aids in examining party-specific trends in media coverage

Figure A.5: portrays the disparity in the share of media mentions between average female and male candidates, stratified by topic, utilizing a dumbbell chart. The chart illustrates the variance, highlighting gender-specific emphasis in media coverage. Each 'dumbbell' encapsulates the comparative media attention, offering a visual representation of the gender dynamics in topic-specific media discourse (including party leaders).

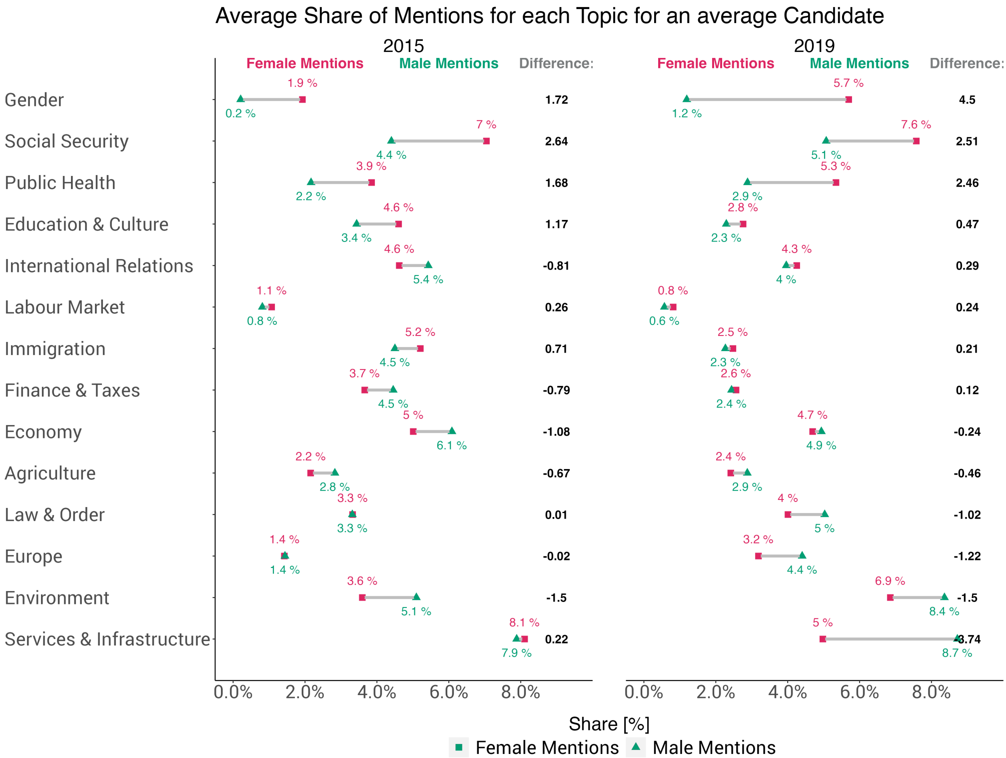

Figure A.6: Portrays the disparity in the share of media mentions between average female and male incumbent candidates, stratified by topic, utilizing a dumbbell chart. The chart illustrates the variance, highlighting gender-specific emphasis in media coverage (Including Incumbents only).

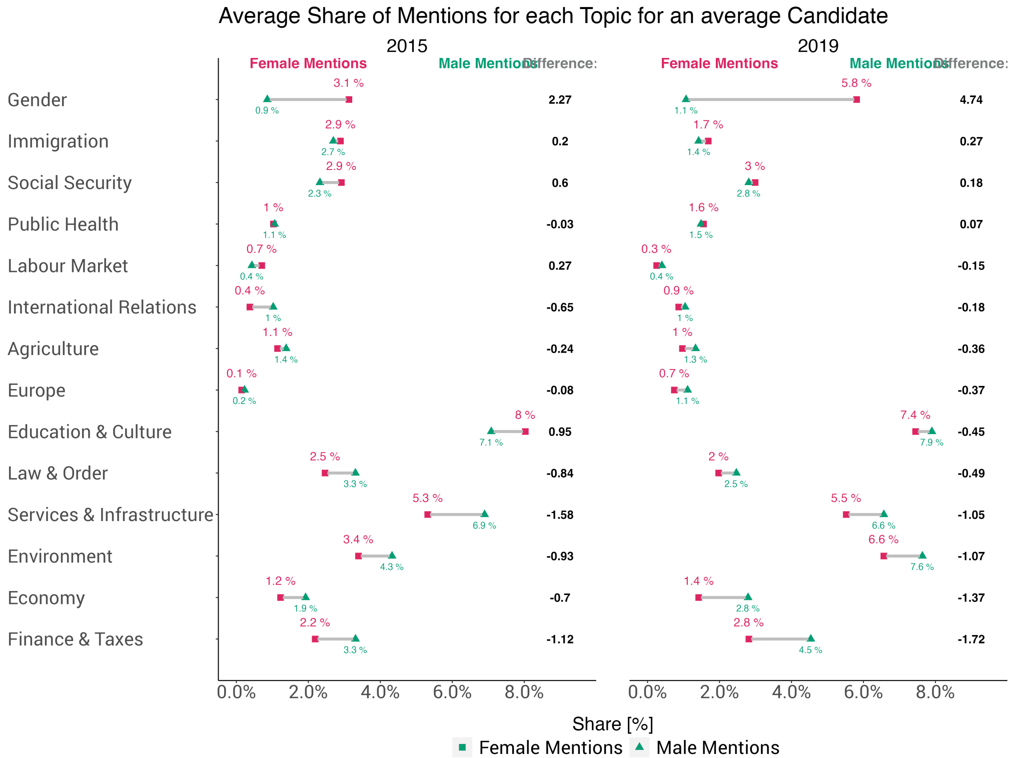

Figure A.7: Illustrates the distribution of media mentions between average female and male non-incumbent candidates across various topics, rendered in a dumbbell (Including Non-Incumbents only).

	Overall	Overall	Gender	Environment	Europe	Immigration
Strike Year (2019)	0.65***	0.65***	5.42*	4.09***	0.55	−1.68
	(0.08)	(0.08)	(2.44)	(0.74)	(1.17)	(0.97)
After women's strike	0.10	0.09	−4.97	2.52	0.81	−0.11
	(0.20)	(0.19)	(6.03)	(1.83)	(2.89)	(2.39)
Strike Year (2019) * After Women Strike	−0.14	−0.14	−0.06	−0.46	−4.07*	1.89
	(0.12)	(0.12)	(3.59)	(1.09)	(1.72)	(1.42)
(Intercept)	1.44***	1.35***	9.82**	5.53***	3.71*	6.32***
	(0.10)	(0.12)	(3.75)	(1.14)	(1.80)	(1.49)
Month FEs	✓	✓	✓	✓	✓	✓
Weekdasy FEs		✓	✓	✓	✓	✓
R^2	0.32	0.34	0.04	0.15	0.04	0.06
Adj. R^2	0.31	0.32	0.01	0.12	0.01	0.03
Num. obs.	610	610	610	610	610	610

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A.5: Statistical OLS models of the share of articles mentioning at least one female candidate. Robustness check for Table 2 with share of all articles, rather than only those mentioning candidates.

	Overall	Overall	Gender	Environment	Europe	Immigration
After women's strike	0.92	0.85	−7.26	4.82	3.92	9.45
	(2.76)	(2.76)	(14.85)	(7.36)	(8.17)	(9.75)
(Intercept)	29.88***	30.62***	22.21*	21.89***	29.32***	13.94*
	(1.34)	(1.72)	(9.26)	(4.59)	(5.09)	(6.08)
Month FEs	✓	✓	✓	✓	✓	✓
Weekdays FEs		✓	✓	✓	✓	✓
R^2	0.10	0.11	0.08	0.07	0.09	0.11
Adj. R^2	0.06	0.06	0.03	0.01	0.03	0.06
Num. obs.	305	305	305	305	305	305

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A.6: Statistical models of the share of articles mentioning at least one female candidate. Robustness check for Table 2 for 2019 data only.

	Overall	Overall	Gender	Environment	Europe	Immigration
Strike Year (2019)	4.70***	4.71***	23.53***	7.05**	5.30*	−6.95*
	(0.77)	(0.77)	(4.39)	(2.41)	(2.66)	(2.71)
After women's strike	−1.41	−1.40	−9.71	4.48	−1.18	−0.18
	(1.91)	(1.92)	(10.84)	(5.96)	(6.57)	(6.70)
Strike Year (2019) * After Women Strike	1.64	1.63	−0.68	0.40	−10.58**	1.95
	(1.14)	(1.14)	(6.45)	(3.55)	(3.91)	(3.99)
(Intercept)	25.79***	25.95***	4.23	20.23***	17.98***	18.24***
	(0.97)	(1.19)	(6.75)	(3.71)	(4.09)	(4.17)
Month FEs	✓	✓	✓	✓	✓	✓
Weekdays FEs		✓	✓	✓	✓	✓
R^2	0.16	0.17	0.13	0.06	0.04	0.07
Adj. R^2	0.14	0.14	0.10	0.03	0.01	0.04
Num. obs.	610	610	610	610	610	610

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A.7: Statistical models of the share of articles mentioning at least one female candidate. Robustness check for Table 2 using a subset of 38 over-regional newspapers.

	Model 1a	Model 1b	Model 2a	Model 2b	Model 2c	Model 2d
Male	0.16*	0.19*	0.16**	0.15*	0.19	0.18**
	(0.07)	(0.08)	(0.06)	(0.06)	(0.14)	(0.06)
Council of States			2.21***	2.18***	0.63***	2.76***
			(0.17)	(0.16)	(0.14)	(0.22)
Top list			−0.04***	−0.04***	−0.02	−0.04***
			(0.01)	(0.01)	(0.02)	(0.01)
incumbent			2.77***	2.74***		
			(0.14)	(0.13)		
(Intercept)	3.24***	3.25***	2.18***	2.36***	5.96***	2.08***
	(0.16)	(0.18)	(0.15)	(0.21)	(0.41)	(0.16)
Multilevel		✓		✓		
Party FEs	✓	✓	✓	✓	✓	✓
Cantonal FEs			✓		✓	✓
AIC	28607.58	28579.08	26970.54	27019.14	2778.15	24029.17
BIC	28663.28	28640.96	27199.51	27099.59	2894.47	24250.03
Log Likelihood	−14294.79	−14279.54	−13448.27	−13496.57	−1353.08	−11978.58
Deviance	4238.06		4119.38		222.25	3875.34
Num. obs.	3599	3599	3599	3599	187	3412
Num. groups: canton		26		26		
Var: canton (Intercept)		0.11		0.56		

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A.8: Statistical negative binomial models of important predictors of media coverage for 2019 only as a Robustness check for Table 3. Model 1a is the baseline model controlling for the party effect of the gender gap. Model 2a displays the effect of media coverage with all important predictors, while 2c displays the effect for the same predictors looking only at the incumbents and 2d for all non-incumbents. Both model 1b and model 2b are the same models using a multilevel approach with the cantons as level two variables.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Male	0.26**	0.32***	0.43***	0.43***	0.16	0.45***
	(0.09)	(0.09)	(0.07)	(0.08)	(0.12)	(0.08)
2019	0.12	0.14	0.08	0.08	0.25	0.07
	(0.09)	(0.09)	(0.08)	(0.08)	(0.14)	(0.08)
Male*2019	−0.14	−0.12	−0.30**	−0.29**	−0.03	−0.30**
	(0.12)	(0.12)	(0.10)	(0.10)	(0.16)	(0.10)
Council of States			2.13***	2.13***	0.51***	2.67***
			(0.15)	(0.14)	(0.10)	(0.20)
Top list			−0.04***	−0.04***	−0.04*	−0.05***
			(0.00)	(0.00)	(0.02)	(0.00)
incumbent			2.76***	2.74***		
			(0.11)	(0.10)		
(Intercept)	2.53***	2.37***	1.81***	1.70***	5.05***	1.79***
	(0.13)	(0.17)	(0.13)	(0.19)	(0.26)	(0.14)
Multilevel		✓		✓		
Party FEs	✓	✓	✓	✓	✓	✓
Cantonal FEs			✓		✓	✓
AIC	43067.72	42969.06	40620.87	40678.14	5094.52	35019.96
BIC	43142.28	43050.39	40885.18	40779.80	5244.94	35275.16
Log Likelihood	−21522.86	−21472.53	−20271.43	−20324.07	−2509.26	−17471.98
Deviance	6934.64		6852.02		453.68	6316.72
Num. obs.	6486	6486	6486	6486	387	6099
Num. groups: canton		26		26		
Var: canton (Intercept)		0.23		0.58		

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A.9: Statistical negative binomial models of important predictors of media coverage for a subset of 38 widely served newspapers as a Robustness check for Table 3. Model 1a is the baseline model controlling for the party effect of the gender gap. Model 2a displays the effect of media coverage with all important predictors, while 2c displays the effect for the same predictors looking only at the incumbents and 2d for all non-incumbents. Both model 1b and model 2b are the same models using a multilevel approach with the cantons as level two variables.

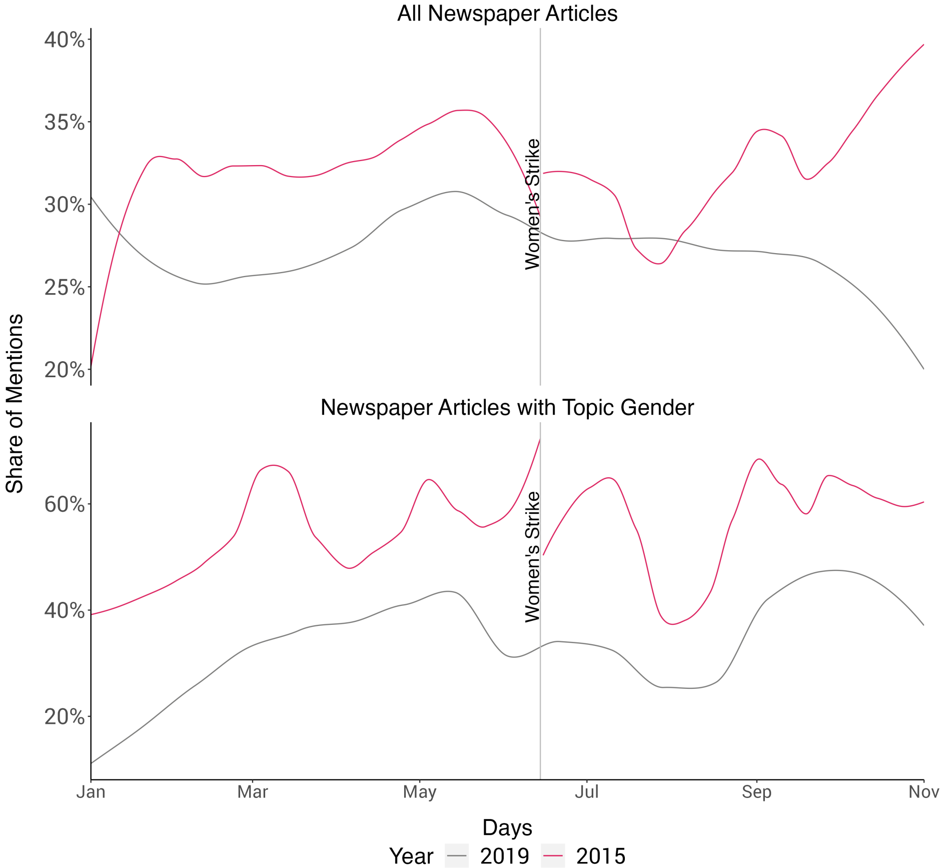

Figure A.8: Depicts trends in daily share of articles covering candidates that mentioned at least one female candidates before and after the Women's Strike, differentiated by all newspaper articles and those specifically classified within the gender topic. (including party leaders).

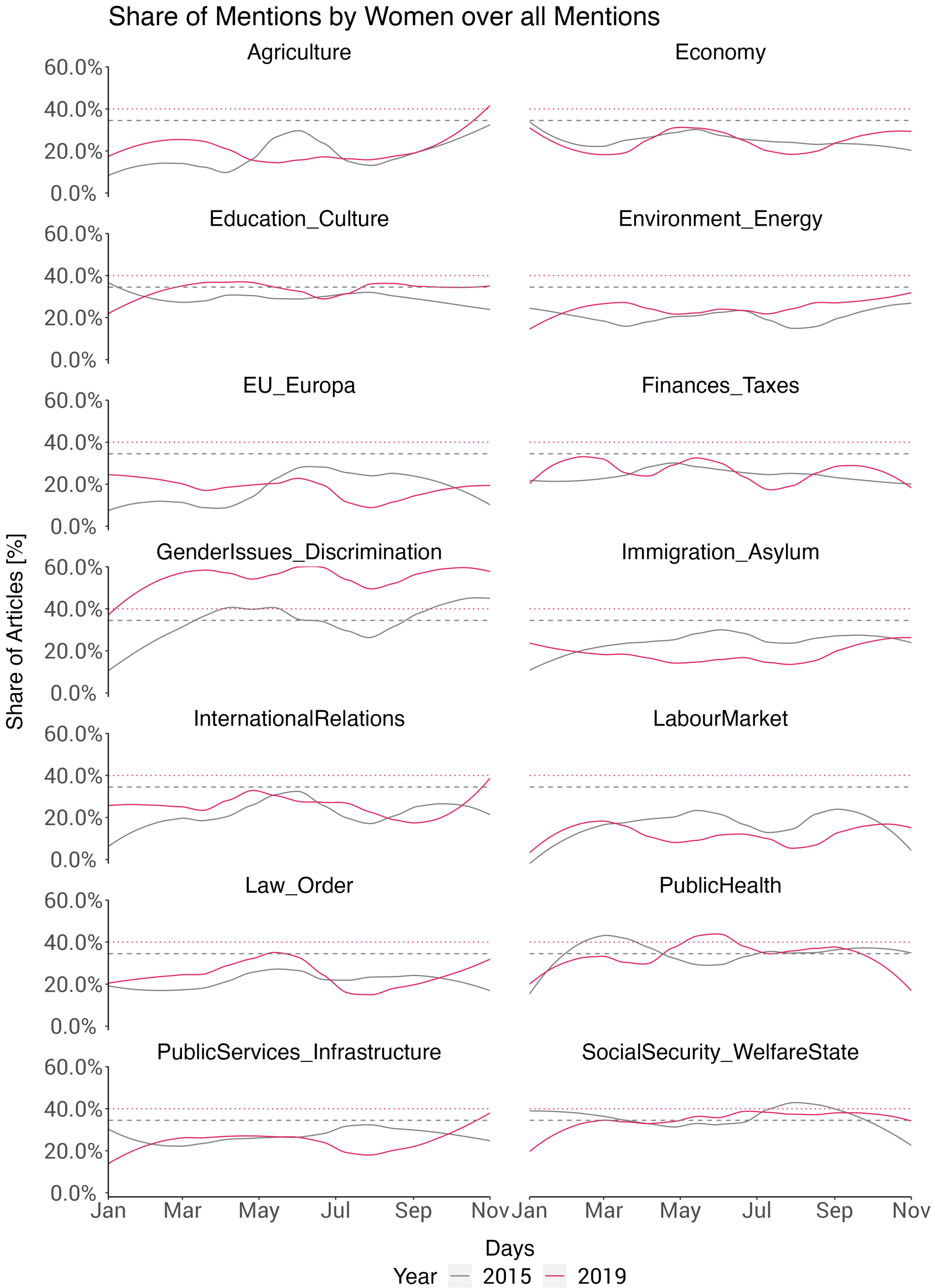

Figure A.9: Timetrend in articles that mention at least one female candidate by Topic. The dotted lines show the share of women to give a (simplified) assessment on the over- or underrepresentation of women in reports on each topic. In contrast to the Figure in the main text, we do not separate the trend line based on the women's strike which leads to smoother estimates.

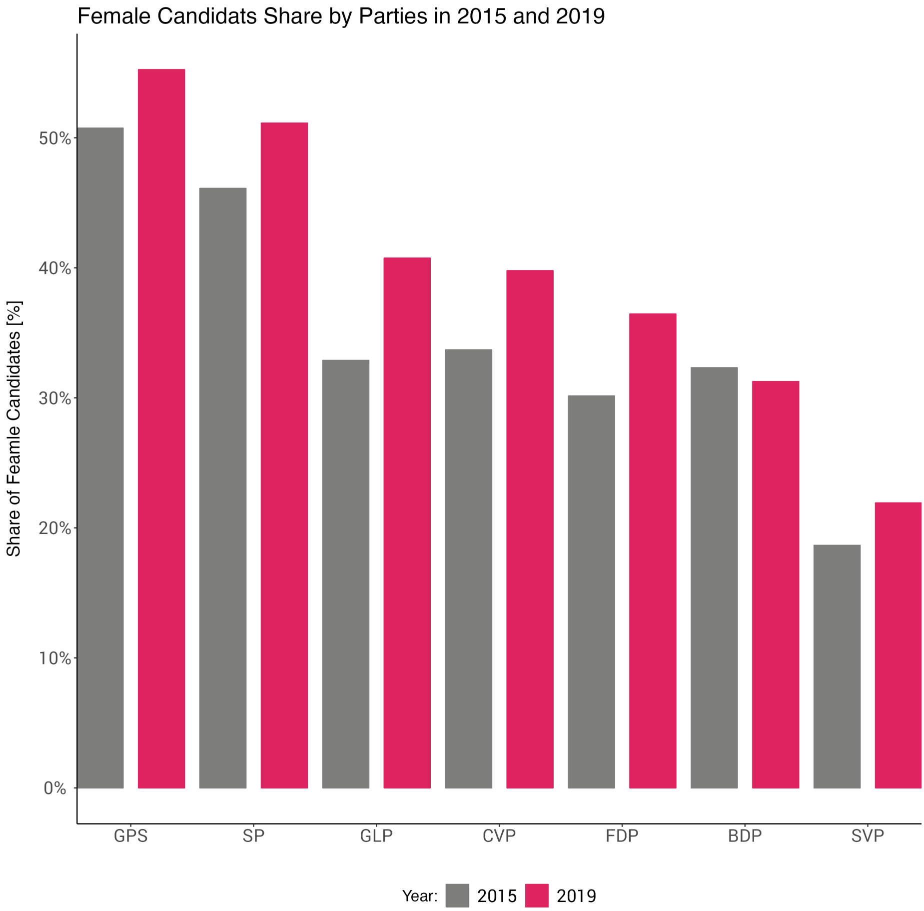

Figure A.10: This faceted bar plot depicts the proportion of female candidates in the Swiss national elections for 2015 and 2019. The two facets represent each election year, allowing for direct comparison between the two-time points. Each bar's height indicates the percentage of female candidates.

Figure A.11: This faceted bar plot illustrates the percentage of female candidates and parliamentarians in the Swiss National Council, broken down by party and charted over multiple election years. Each facet represents a different political part.

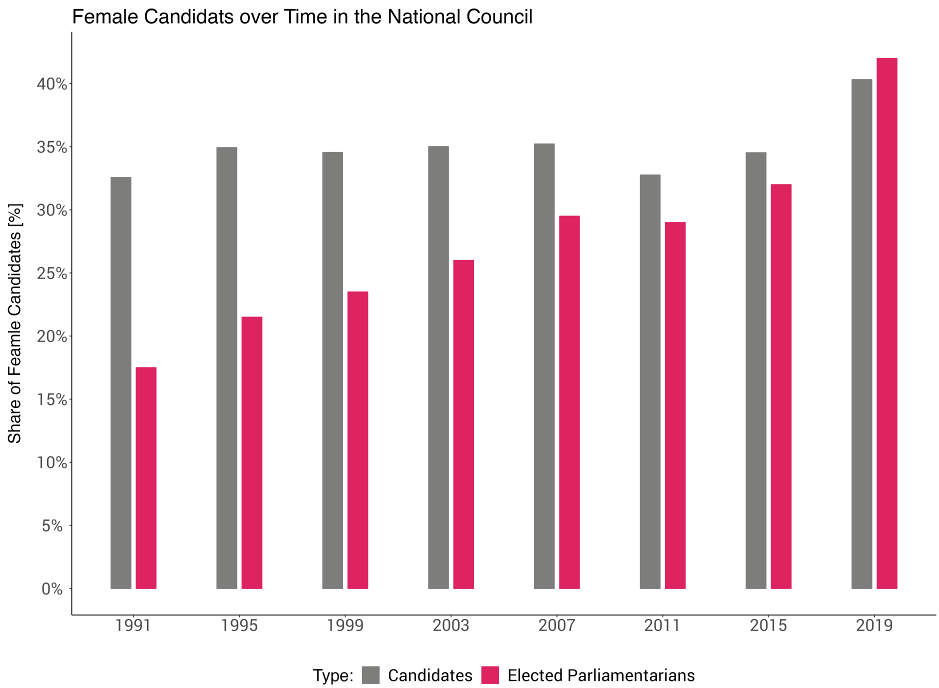

Figure A.12: This bar plot presents a side-by-side comparison of the share of female candidates versus the actual share of females who secured seats in the Swiss National Council over multiple election years. For each election year, two adjacent bars represent the proportion of female candidates and the proportion of elected female parliamentarians, respectively.

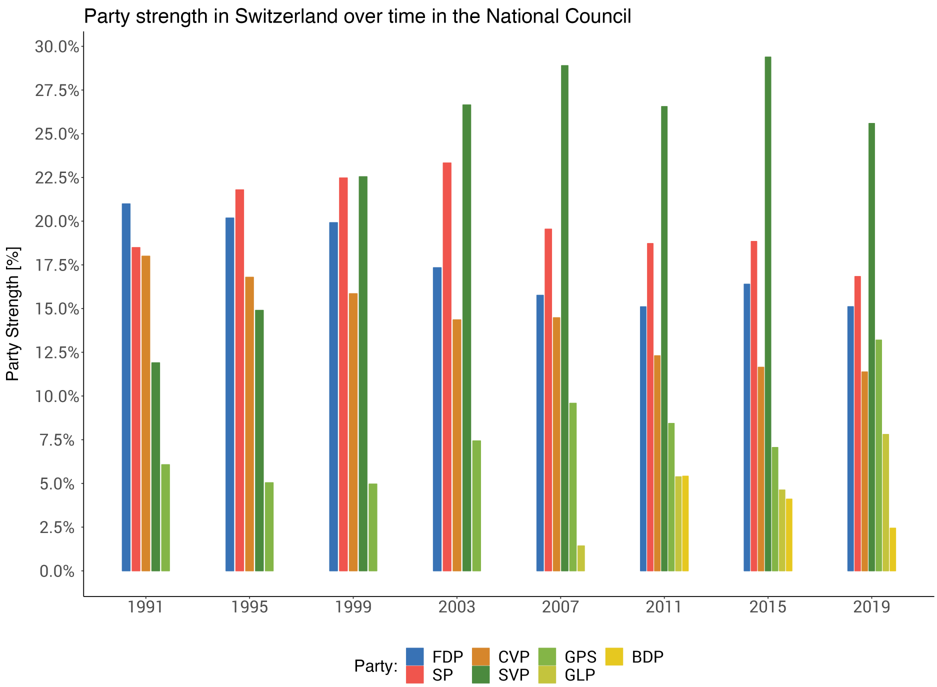

Figure A.13: This bar plot showcases the evolution of party strength in the Swiss political landscape over multiple election years.

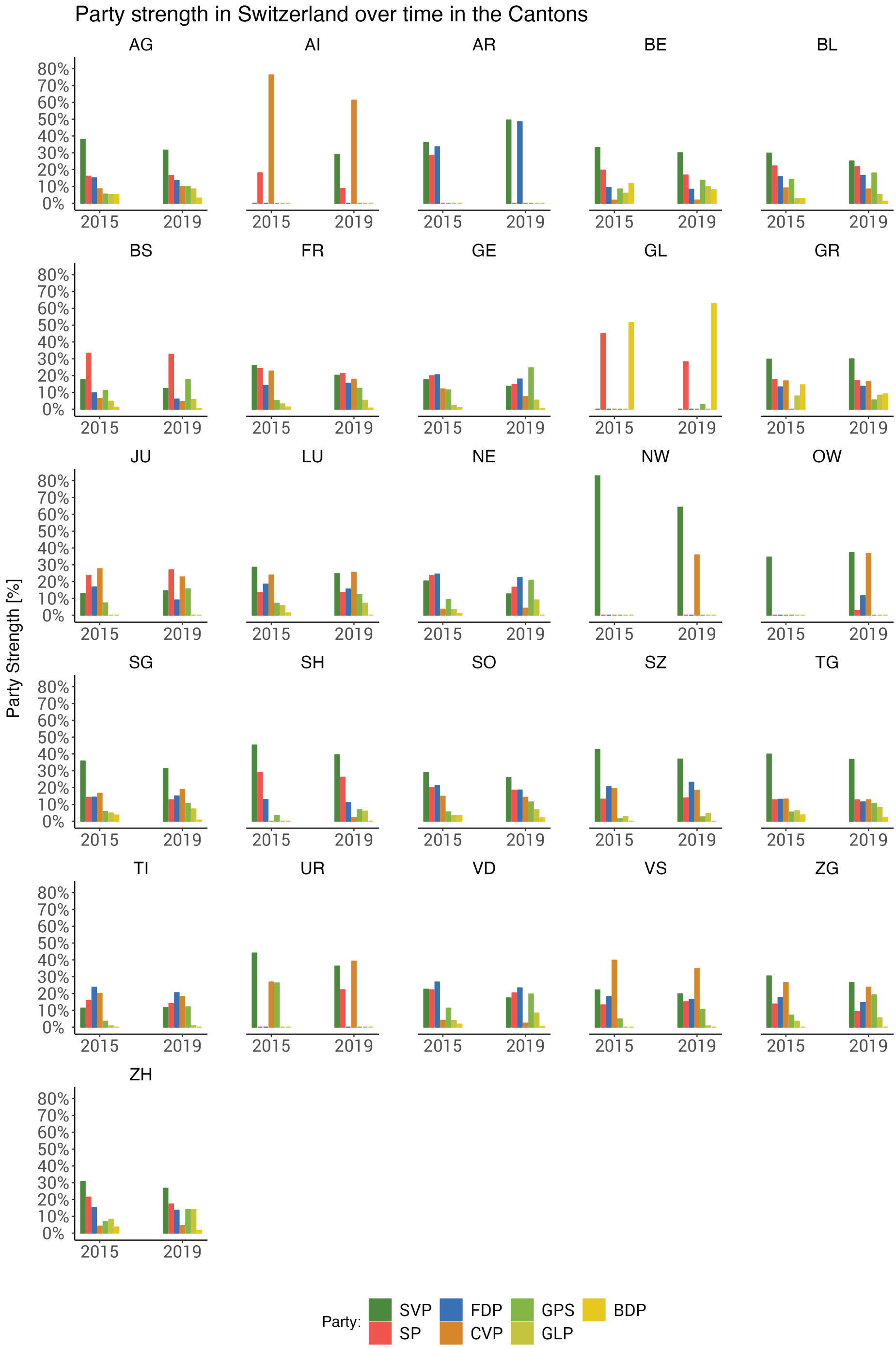

Figure A.14: This bar plot showcases the evolution of party strength in the Swiss political landscape over the 2015 and 2019 election years faceted by Canton.

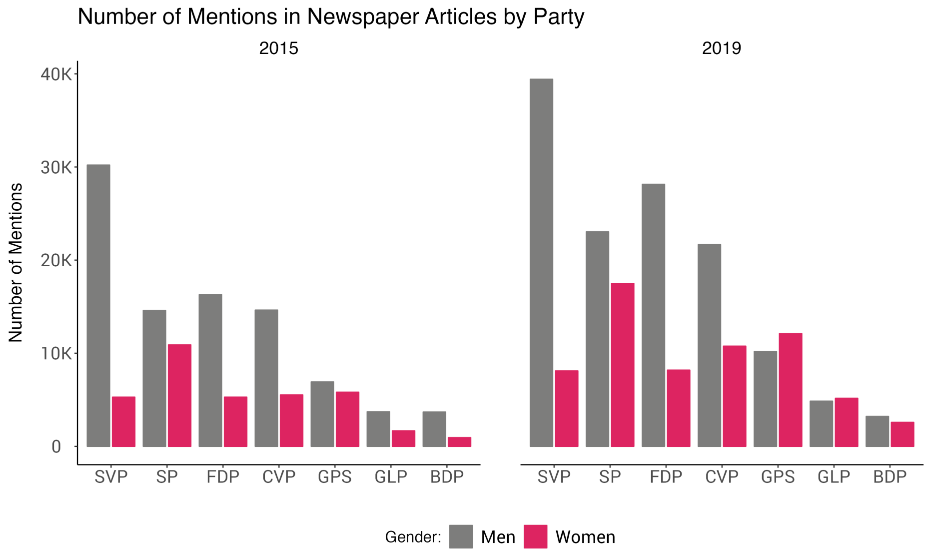

Figure A.15: This bar plot provides a detailed visualization of the number of mentions for various political parties in Swiss newspapers, faceted for 2015 and 2019. Within each facet, individual bars represent the number of mentions for each party, further grouped by gender. Specifically, each party has two adjacent bars — one for male mentions and the other for female mentions.

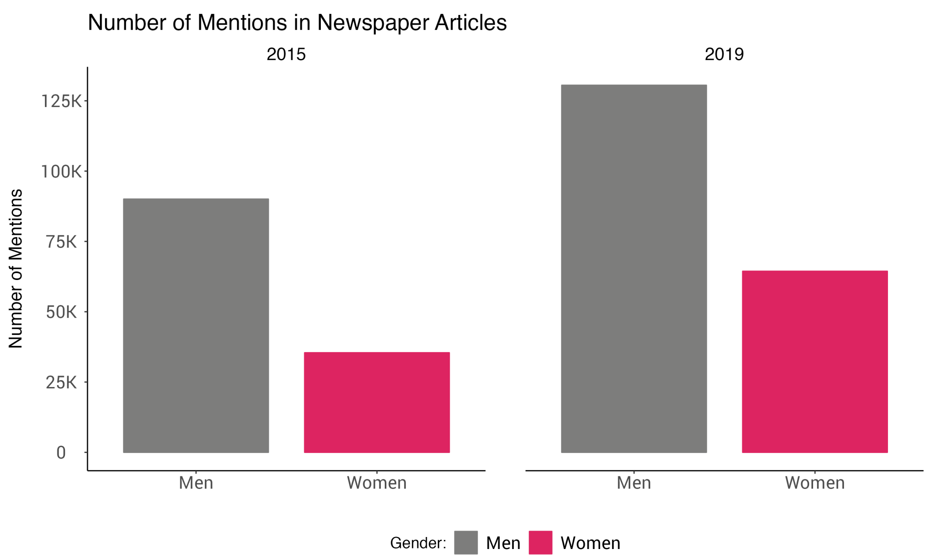

Figure A.16: This bar plot provides a summarized visualization of the number of mentions of female and male candidates in Swiss newspapers, faceted for 2015 and 2019.

E. Newspaper Corpus

Our sample is notably extensive, including a diverse array of media outlets, ranging from hyper-local publications catering to specific small regions and communities to widely circulated newspapers that command a substantial readership across the French and German-speaking regions of Switzerland. This inclusion of heterogeneous sources helps to provide a holistic picture of the media landscape.

However, we must acknowledge a limitation in our sample – the absence of newspapers from the Italian-speaking region of Switzerland. Despite our efforts to ensure a representative and comprehensive dataset, we encountered challenges in accessing a sufficient number of sources from this linguistic region. The hurdles related to the availability and accessibility of archived articles and publications resulted in our inability to incorporate a representative sample from the Italian-speaking cantons.

We recognize that this limitation might impact the completeness of our study. Nevertheless, we can map the Swiss media landscape, for the most part, very reliably. The only newspaper of greater importance missing in the dataset is the Baslerstab (which was only published until 2014). All other relevant sources are included in the corpus for both 2019 and 2015.

Table A.10: Number of Articles per Newspaper.

Newspaper	Total	Daily Average	Daily min	Daily max	Widely Read Newspaper
20 minuten	145831	239.854	17	490	✓
24 heures	87595	144.071	8	511	✓
Aargauer Zeitung	62939	135.937	8	539	✓
Agefi	17257	45.653	1	153	
Anzeiger von Uster	2107	4.172	1	36	
Appenzeller Zeitung	28599	113.04	71	466	
Arcinfo	30538	60.591	29	220	
Badener Tagblatt	111	1.22	1	3	
Basellandschaftliche Zeitung	20580	50.565	7	193	
Basler Zeitung	86744	143.379	1	494	✓
Berner Oberländer	22566	89.194	60	367	
Berner Zeitung	108172	177.914	4	548	✓
Bieler Tagblatt	26597	56.35	1	298	
Bilanz online	1799	3.657	1	32	
Blick	30212	59.826	32	326	✓
Blick am Abend	13152	62.928	48	112	
Bote der Urschweiz	42291	84.582	36	229	
Bündner Tagblatt	32477	64.057	23	268	✓
Cash Online	90428	154.051	1	960	
Coopzeitung	9815	112.816	36	184	
Das Magazin	1147	14.519	2	52	
Der Bund	76049	125.081	5	597	✓
Der Landbote	42051	83.269	53	356	✓
Die Südostschweiz	1464	104.571	88	121	
Die Weltwoche	6474	78	55	179	✓
Die Wochenzeitung	3591	44.888	29	103	✓
Finanz und Wirtschaft	22032	42.288	1	125	✓
Freiburger Nachrichten	29444	58.653	22	291	
Furttaler	3174	36.483	17	66	
GHI	2628	31.286	1	52	
Glattaler	3529	41.035	18	86	

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Table A.10: Number of Articles per Newspaper

Newspaper	Total	Daily Average	Daily min	Daily max	Widely Read Newspaper
Glückspost	6676	78.541	65	95	
Handelszeitung	12021	20.619	1	127	
Infosperber	1775	2.919	1	23	
Journal de Morges	1935	46.071	23	92	
L'Hebdo	2806	65.256	45	157	
L'Illustré	3145	36.149	17	111	
La Broye	5175	61.607	29	110	
La Liberté	45160	89.96	56	253	✓
Le Journal du Jura	27716	59.096	2	207	
Le Matin	56230	92.789	3	487	✓
Le Matin Dimanche	9780	112.414	70	193	✓
Le Nouvelliste	34554	68.833	34	273	
Le Temps	24940	49.583	1	229	✓
Limmattaler Zeitung	21178	45.84	4	315	
Luzerner Zeitung	34100	135.317	62	1336	✓
Medienwoche	332	1.573	1	9	
Migros-Magazin	10693	124.337	73	165	
Neue Luzerner Zeitung	38498	152.166	1	488	✓
Neue Zürcher Zeitung	59868	118.55	57	460	✓
Nidwaldner Zeitung	25060	101.048	65	507	
NZZ am Sonntag	12782	146.92	102	216	✓
Obersee Nachrichten	3913	47.145	24	92	
Obwaldner Zeitung	25307	101.228	64	501	
Oltner Tagblatt	16482	35.83	7	81	
Ostschweiz am Sonntag	6119	87.414	57	128	✓
Rümlanger	2340	26.897	7	74	
Schweiz am Sonntag	11501	261.386	210	378	✓
Schweizer Bauer	14206	84.059	51	238	
Schweizer Familie	3465	42.256	24	65	
Schweizer Illustrierte	4690	53.908	33	223	
Seetaler Bote	6304	74.165	19	243	
SI Sport	28	28	28	28	
Solothurner Zeitung	30670	66.385	22	504	
Sonntagsblick	10019	115.161	80	202	✓
SonntagsZeitung	9353	107.506	80	150	✓
srf.ch	84173	138.442	36	1732	✓
St. Galler Tagblatt	90896	179.282	75	637	✓
Südostschweiz	41160	83.489	33	323	✓
swissinfo.ch	6266	10.531	1	100	✓
Tagblatt der Stadt Zürich	3618	41.586	24	112	✓
Tages-Anzeiger	114624	188.526	40	582	✓
TagesWoche	1154	29.59	1	84	
TagesWoche Online	3654	11.98	1	115	
Thurgauer Zeitung	55277	109.028	50	418	
Toggenburger Tagblatt	27764	110.175	67	427	
Tribune de Genève	102675	168.873	27	677	✓
Urner Zeitung	24766	99.462	37	487	
Volketswiler	705	8.198	1	25	
Walliser Bote	37911	75.52	43	286	
watson.ch	18303	51.269	1	477	✓
Werdenberger & Obertoggenburger	36939	73.002	14	457	

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Table A.10: Number of Articles per Newspaper

Newspaper	Total	Daily Average	Daily min	Daily max	Widely Read Newspaper
Willisauer Bote	13609	79.122	26	198	
Zentralplus	11274	18.604	2	109	
Zentralschweiz am Sonntag	6404	91.486	60	124	
Zofinger Tagblatt	27680	59.784	16	366	
Zuger Zeitung	26734	106.936	59	514	
Zürcher Oberlander	37109	73.483	42	366	
Zürcher Unterländer	32377	64.113	25	360	
Zürichsee-Zeitung	42815	84.782	46	357	

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