All Women Short lists Methodology

TO DO:

2. Male MP topic models matching

Methodology

Previous research on gender differences in political speech patterns has focused on differences between male and female politicians (Yu 2014) or on variations in Hilary Clinton's speech patterns (Jones 2016; Bligh et al. 2010). This paper focuses on differences in speech patterns between female Labour MPs nominated through All Women Shortlists (AWS) and female Labour MPs nominated through open short lists. We examined differences in speaking styles using the `Linguistic Inquiry and Word Count 2015` (LIWC) dictionary (Pennebaker et al. 2015) and the `spaCy` (Honnibal and Montani 2017) Parts-of-Speech (POS) tagger. We examined differences in the topics discussed by AWS and non-AWS MPs, using χ^2 tests for individual words and for bigrams. We experimented with unsupervised Latent Dirichlet Allocation (Blei, Ng, and Jordan 2003), and trained a Naive Bayes classifier to distinguish AWS and non-AWS speeches.

To account for the possible effects of age, parliamentary experience and cohort, and in order to compare women selected through all women short lists to women who were not (but who theoretically had the opportunity to contest all-women short lists), our analysis is been restricted only to Labour MPs first elected to the House of Commons in the 1997 General Election, up to but excluding the 2017 General Election. Comparisons between MPs of different parties are also restricted to MPs first elected in the 1997 General Election, and before the 2017 General Election. Speeches made by the Speaker, including Deputy Speakers, were also excluded. Words contained in parentheses were removed, as they are added by Hansard to provide additional information not actually spoken by the MP.[1] Speeches and MP data is from a previously assembled dataset (Odell 2018). Information on candidates selected through all women short lists is from the House of Commons Library (Kelly 2016). Unsuccessful General Election candidates selected through all women short lists who were subsequently elected in a byelection are classified as having been selected on an all women short list.

Word classification used the `Linguistic Inquiry and Word Count 2015` (LIWC) dictionary (Pennebaker et al. 2015) and tokenising tools from the `Quanteda` R package (Benoit 2018). Word counts and words-per-sentence were calculated using `stringi` (Gagolewski 2018), a wrapper to the ICU regex library.

Following Yu (2014) drawing on (Newman et al. 2008) we used the following LIWC categories:

- All Pronouns (pronoun)
- First person singular pronouns (i)
- First person plural pronouns (we)
- Verbs (verb)
- Auxiliary verbs (auxverb)
- Social processes (social)
- Positive emotions (posemo)
- Negative emotions (negemo)
- Tentative words (tentat)
- Articles (article)
- Prepositions (preps)
- Anger words (anger)
- Swear words (swear)
- Cognitive processes (cogproc)

[1] e.g. a reference to "the member for Bethnal Green and Bow" in keeping with Parliamentary convention of identifying MPs by their seat rather than their name would be followed by "(Rushnara Ali)".

Table 1: Labour MPs and Intakes

General Election	Total MPs	Labour MPs	Female Labour MPs	Labour MPs Intake	Intake Women	Intake Short list	Nominated Short list
1997	659	418	101 (24%)	177	64 (36%)	35	38
2001	659	412	95 (23%)	38	4 (11%)	0	0
2005	646	355	98 (28%)	40	26 (65%)	23	30
2010	650	258	81 (31%)	64	32 (50%)	28	63
2015	650	232	99 (43%)	49	31 (63%)	31	77

Table 2: Number of Speeches and Words in Dataset

Gender	Speeches	Words
All	656412	111180398
Female	148702	26231034
Male	507710	84949364
Conservatives		
All	285291	44800169
Female	48768	7363031
Male	236523	37437138
Labour		
All	261942	46494850
Female	84569	15897929
Non-All Women Shortlists	28695	5422776
All Women Shortlists	55874	10475153
Male	177373	30596921
Liberal Democrat		
All	72716	13485902
Female	7552	1503459
Male	65164	11982443
Other		
All	36463	6399477
Female	7813	1466615
Male	28650	4932862

- Words longer than six letters (Sixltr)

We also included mean words-per-sentence (WPS), total speach word count (WC) and Flesch–Kincaid grade level (FK) (Kincaid et al. 1975), calculated using `Quanteda` (Benoit 2018) and `stringi` (Gagolewski 2018).

Descriptive Statistics

Data in this table is from House of Commons library reports (Kelly 2016; Audickas, Hawkins, and Cracknell 2017). All women short lists were not used by Labour during the 2001 General Election.

Women vs Men

There are no categories where gender differences meet the effect size threshold of $|0.2|$ suggested by Cohen (1988, 25–26) to indicate a small effect. 4 categories – words with more than six letters, prepositions, words-per-sentence and Flesh-Kincaid grade level – exceeded the $|0.1|$ threshold suggested by Newman et al (2008).

Table 3: Effect Sizes for Male and Female Labour MPs

	Women		Men		Effect Size	
	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Pronouns	10.07	4.60	10.15	4.99	0.02	negligible
First person singular pronouns	1.89	2.41	2.02	2.55	0.05	negligible
First person plural pronouns	0.97	1.42	0.99	1.51	0.01	negligible
Verbs	12.82	5.00	12.67	5.36	-0.03	negligible
Auxiliary verbs	7.91	3.45	7.93	3.69	0.01	negligible
Social processes	8.47	4.82	8.18	5.11	-0.06	negligible
Positive emotions	2.73	2.49	2.57	2.54	-0.06	negligible
Negative emotions	1.15	1.68	1.07	1.77	-0.05	negligible
Tentative words	1.48	1.74	1.58	1.90	0.05	negligible
More than six letters	10.58	3.68	10.22	3.92	-0.10	negligible
Articles	7.65	3.30	7.96	3.55	0.09	negligible
Prepositions	12.58	4.42	12.14	4.73	-0.10	negligible
Anger words	0.23	0.81	0.24	0.77	0.01	negligible
Swear words	0.00	0.06	0.00	0.09	0.01	negligible
Cognitive processes	8.68	4.83	8.82	5.15	0.03	negligible
Words per Sentence	43.63	19.68	41.15	20.04	-0.13	negligible
Total Word Count	402.79	691.27	370.18	647.36	-0.05	negligible
Flesh-Kincaid Grade Level	10.81	7.68	9.78	7.87	-0.13	negligible

Short lists vs Non-Short lists

The following plots show changes in the occurences of selected LIWC terms, words-per-sentence, total word count and Flesch–Kincaid grade level, over the course of an MP's career. There do not appear to be any notable changes in speaking style over the course of female Labour MPs' careers.

There are no categories among female Labour MPs by selection process meeting the $|0.2|$ threshold. Only one category – first person plural pronouns, d=0.19 – exceeded $|0.1|$.

Conservatives vs Labour

There are no categories with effect sizes exceeding $|0.2|$ between Labour and Conservative MPs, like inter-Labour differences.

All MPs Gender Differences

POS Analysis

Part-of-speech (POS) tagging was done using `spaCy` (Honnibal and Montani 2017) and the `spacyr` package (Benoit and Matsuo 2018).

Tokenising / Keyness

The most commonly used words by both men and women would be protocol decorum expressions, so we calculate the keyness of words to identify gender differences in the choices of topics raised by men and women, and by short-list and non-short list women.

Table 4: Effect Sizes for Female Labour MPs by selection process

	All Women Short lists		Open Shorlists		Effect Size	
	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Pronouns	10.01	4.67	10.19	4.48	-0.04	negligible
First person singular pronouns	1.86	2.41	1.95	2.42	-0.04	negligible
First person plural pronouns	0.88	1.36	1.16	1.51	-0.19	negligible
Verbs	12.88	5.10	12.69	4.80	0.04	negligible
Auxiliary verbs	7.94	3.49	7.86	3.38	0.02	negligible
Social processes	8.48	4.94	8.46	4.59	0.00	negligible
Positive emotions	2.69	2.52	2.81	2.42	-0.05	negligible
Negative emotions	1.16	1.69	1.13	1.67	0.02	negligible
Tentative words	1.48	1.75	1.49	1.73	0.00	negligible
More than six letters	10.52	3.73	10.70	3.58	-0.05	negligible
Articles	7.69	3.38	7.55	3.15	0.04	negligible
Prepositions	12.55	4.54	12.63	4.15	-0.02	negligible
Anger words	0.23	0.78	0.24	0.88	-0.01	negligible
Swear words	0.00	0.06	0.00	0.05	0.01	negligible
Cognitive processes	8.59	4.90	8.86	4.69	-0.06	negligible
Words per Sentence	44.02	20.45	42.85	18.05	0.06	negligible
Total Word Count	401.77	704.40	404.78	664.97	0.00	negligible
Flesh-Kincaid Grade Level	10.97	7.97	10.48	7.06	0.07	negligible

Table 5: Effect Sizes for All Labour and Conservative MPs

	Labour		Conservatives		Effect Size	
	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Pronouns	10.12	4.87	10.62	4.84	0.10	negligible
First person singular pronouns	1.98	2.51	2.15	2.56	0.07	negligible
First person plural pronouns	0.98	1.48	1.22	1.70	0.15	negligible
Verbs	12.72	5.24	12.93	5.13	0.04	negligible
Auxiliary verbs	7.92	3.61	8.17	3.58	0.07	negligible
Social processes	8.28	5.02	8.13	4.80	-0.03	negligible
Positive emotions	2.62	2.53	2.85	2.66	0.09	negligible
Negative emotions	1.10	1.74	1.05	1.78	-0.03	negligible
Tentative words	1.55	1.85	1.57	1.88	0.01	negligible
More than six letters	10.34	3.85	10.28	3.76	-0.02	negligible
Articles	7.86	3.48	7.82	3.45	-0.01	negligible
Prepositions	12.28	4.64	12.38	4.49	0.02	negligible
Anger words	0.24	0.78	0.24	0.82	0.01	negligible
Swear words	0.00	0.08	0.00	0.10	0.00	negligible
Cognitive processes	8.77	5.05	8.86	5.06	0.02	negligible
Words per Sentence	41.95	19.96	42.76	20.16	0.04	negligible
Total Word Count	380.71	662.03	335.54	592.41	-0.07	negligible
Flesh-Kincaid Grade Level	10.12	7.82	10.41	7.91	0.04	negligible

Table 6: Effect Sizes for Male and Female MPs, All Parties

	Women		Men		Effect Size	
	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Pronouns	10.31	4.65	10.26	4.90	-0.01	negligible
First person singular pronouns	1.99	2.45	2.00	2.52	0.00	negligible
First person plural pronouns	1.11	1.57	1.08	1.59	-0.02	negligible
Verbs	12.88	4.97	12.80	5.26	-0.02	negligible
Auxiliary verbs	8.00	3.45	8.08	3.64	0.02	negligible
Social processes	8.45	4.77	8.00	4.93	-0.09	negligible
Positive emotions	2.84	2.53	2.69	2.58	-0.06	negligible
Negative emotions	1.10	1.65	1.08	1.78	-0.01	negligible
Tentative words	1.47	1.73	1.61	1.91	0.08	negligible
More than six letters	19.73	6.94	19.25	7.18	-0.07	negligible
Articles	7.62	3.31	8.00	3.51	0.11	negligible
Prepositions	12.58	4.36	12.22	4.62	-0.08	negligible
Anger words	0.23	0.78	0.25	0.82	0.02	negligible
Swear words	0.00	0.05	0.00	0.10	0.01	negligible
Cognitive processes	8.67	4.79	8.93	5.12	0.05	negligible
Words per Sentence	43.25	19.45	42.06	20.12	-0.06	negligible
Total Word Count	377.31	648.92	358.13	623.49	-0.03	negligible
Flesh-Kincaid Grade Level	10.63	7.61	10.16	7.89	-0.06	negligible

Table 7: Part-of-Speech Effect Sizes for Male and Female Labour MPs

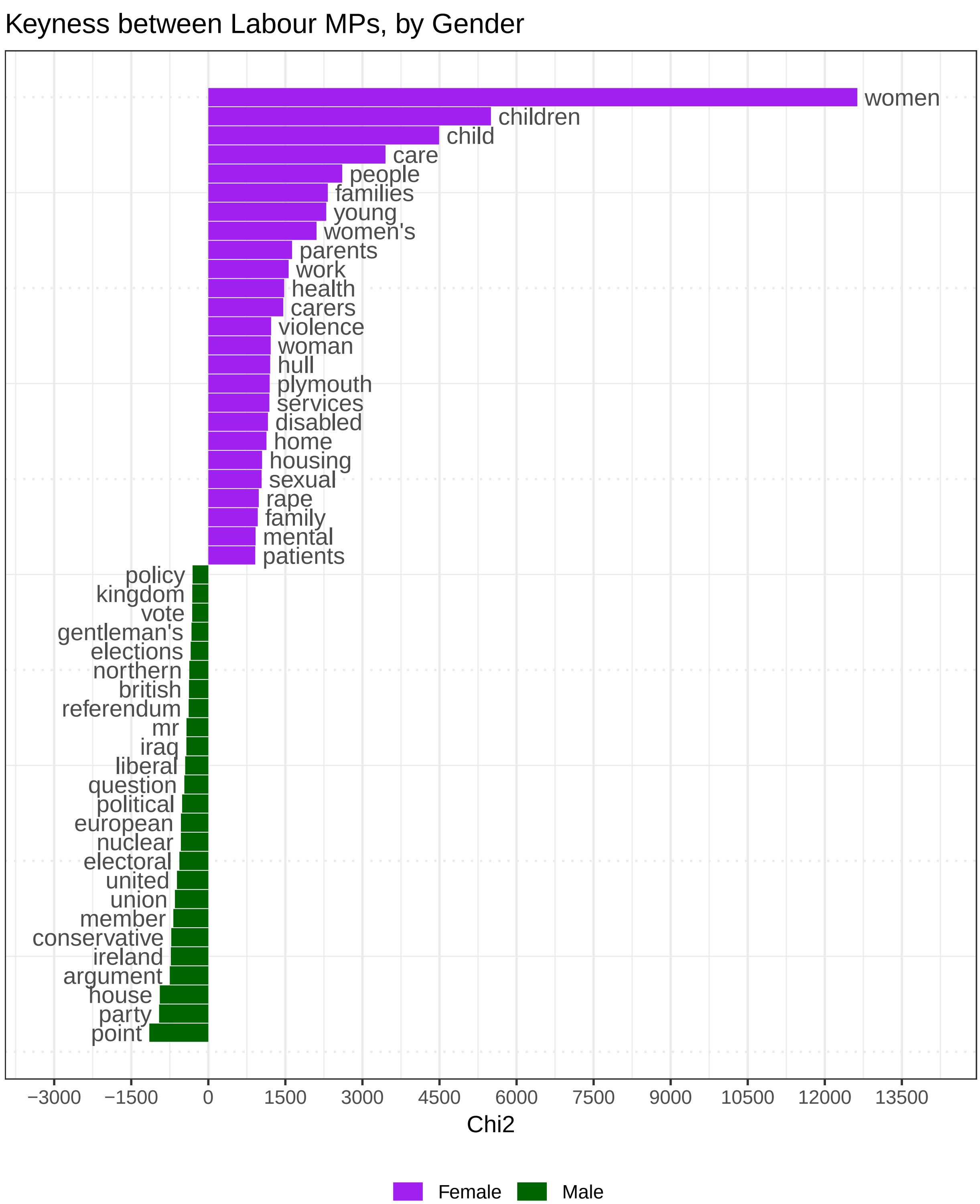
	Women		Men		Effect Size	
Word Type	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Nouns	22.18	9.60	21.66	10.96	-0.04	negligible
Plural Nouns	5.85	3.72	5.03	3.79	-0.16	negligible
Singular Nouns	15.62	9.84	16.01	11.19	0.02	negligible
Adjectives	9.58	4.78	9.28	5.29	-0.02	negligible
Adverbs	4.91	4.26	5.07	4.91	0.03	negligible
Verbs	20.94	9.52	20.78	10.28	-0.02	negligible

Table 8: Part-of-Speech Effect Sizes for AWS and non-AWS Labour MPs

	All Women Short lists		Open Shorlists		Effect Size	
Word Type	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Nouns	22.16	8.78	22.18	10.00	-0.04	negligible
Plural Nouns	6.03	3.60	5.76	3.77	-0.16	negligible
Singular Nouns	15.51	8.97	15.67	10.26	0.02	negligible
Adjectives	9.83	4.59	9.45	4.86	-0.02	negligible
Adverbs	4.95	3.78	4.89	4.49	0.03	negligible
Verbs	20.88	9.04	20.97	9.76	-0.02	negligible

Men vs Women

Keyness – a linguistic measure of the frequency of different words in two groups of texts – reveals clear gender differences in the most disproportionately common words used by female and male Labour MPs. Unsurprisingly, despite male MPs saying almost twice as many words (30601887 vs 15898845) as their female colleagues, female Labour MPs were more than two-and-a-half (2.61) times as likely to say "women". They were also much more likely to refer to "women's" and "woman". Female Labour MPs also appear much more likely to discuss "children", "people", "care", "families", "home", "parents", "work" and social policy areas such as "services", "disabled [people]" and "housing" than their male colleagues. Male MPs were more likely to refer to military topics ("Iraq", "nuclear"), and to parliamentary process and protocol – "question", "political", "conservative", "electoral", "house", "party", "argument" "liberal" and "point" are far more common in speeches by male Labour MPs than by female ones. This could suggest that male MPs are more comfortable using the traditional language of House of Commons debate.

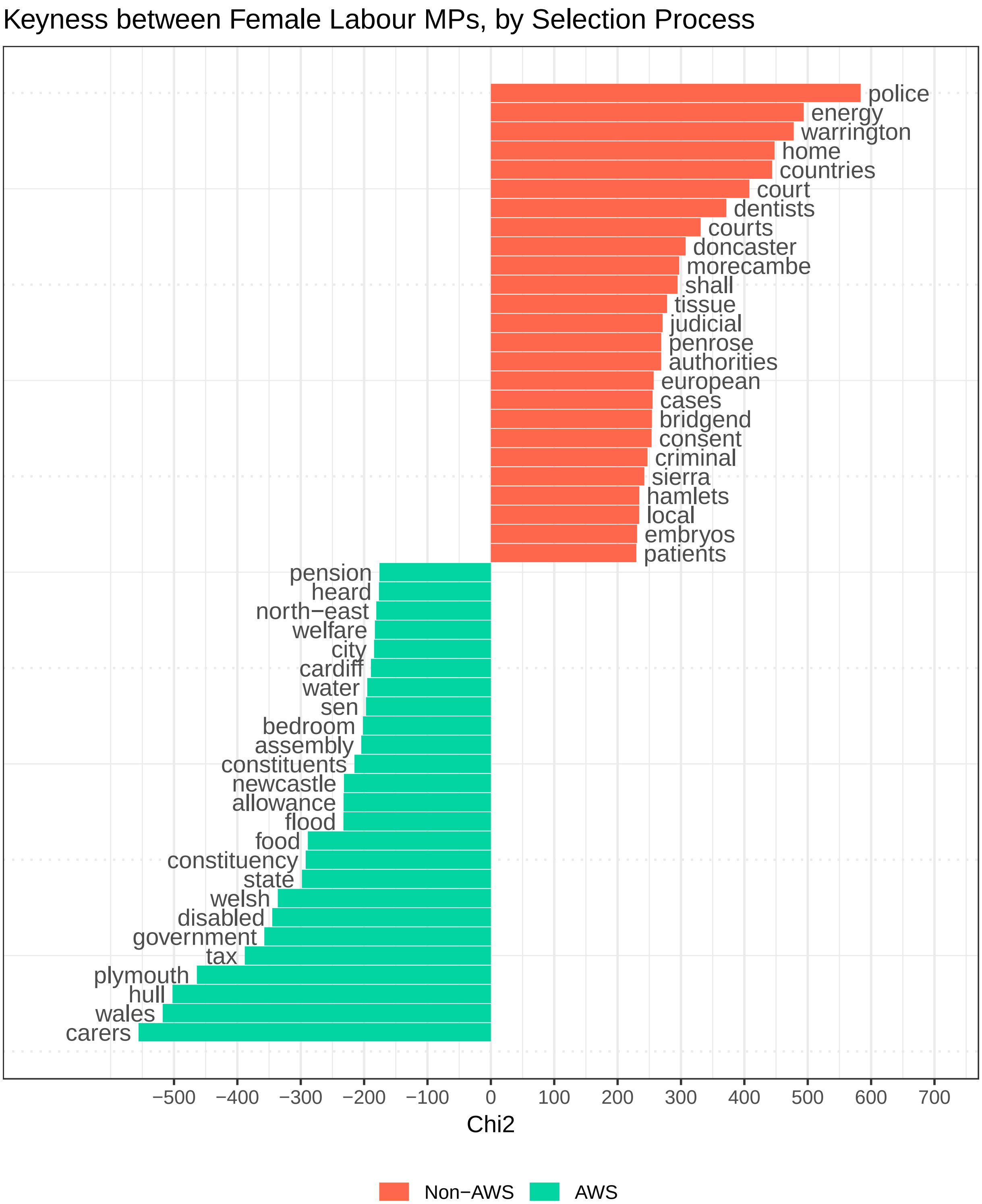


Short lists vs Non-Short lists

Keyness differences by selection process are not as obviously stereotypical. Nonetheless, the most common words amongst AWS MPs included "carers", "disabled", "bedroom" and "sen"[2]. Also of note is AWS MPs

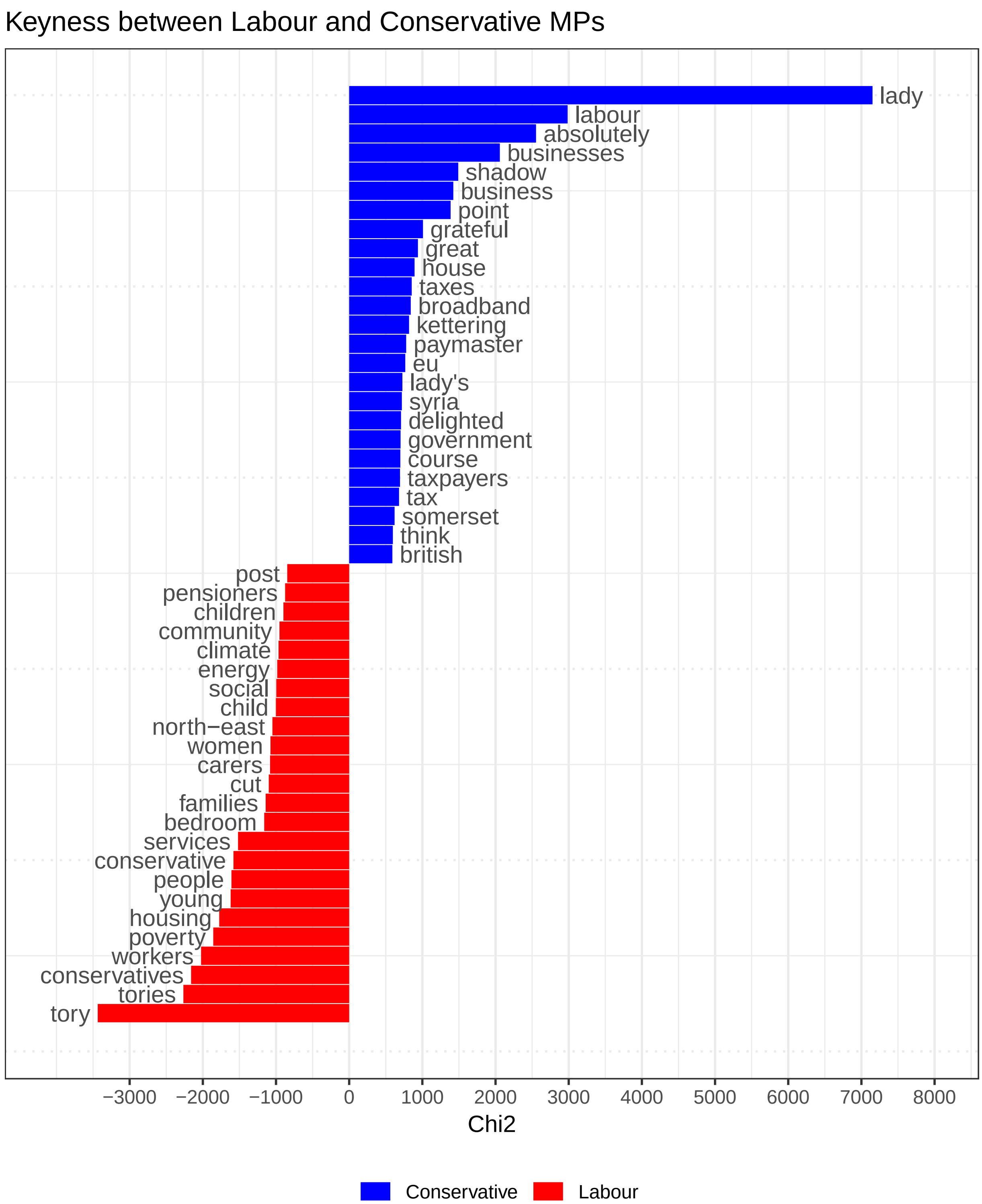
[2] Special Educational Needs

making more references to their “constituency” and its “constituents”, [drawing on representation of]



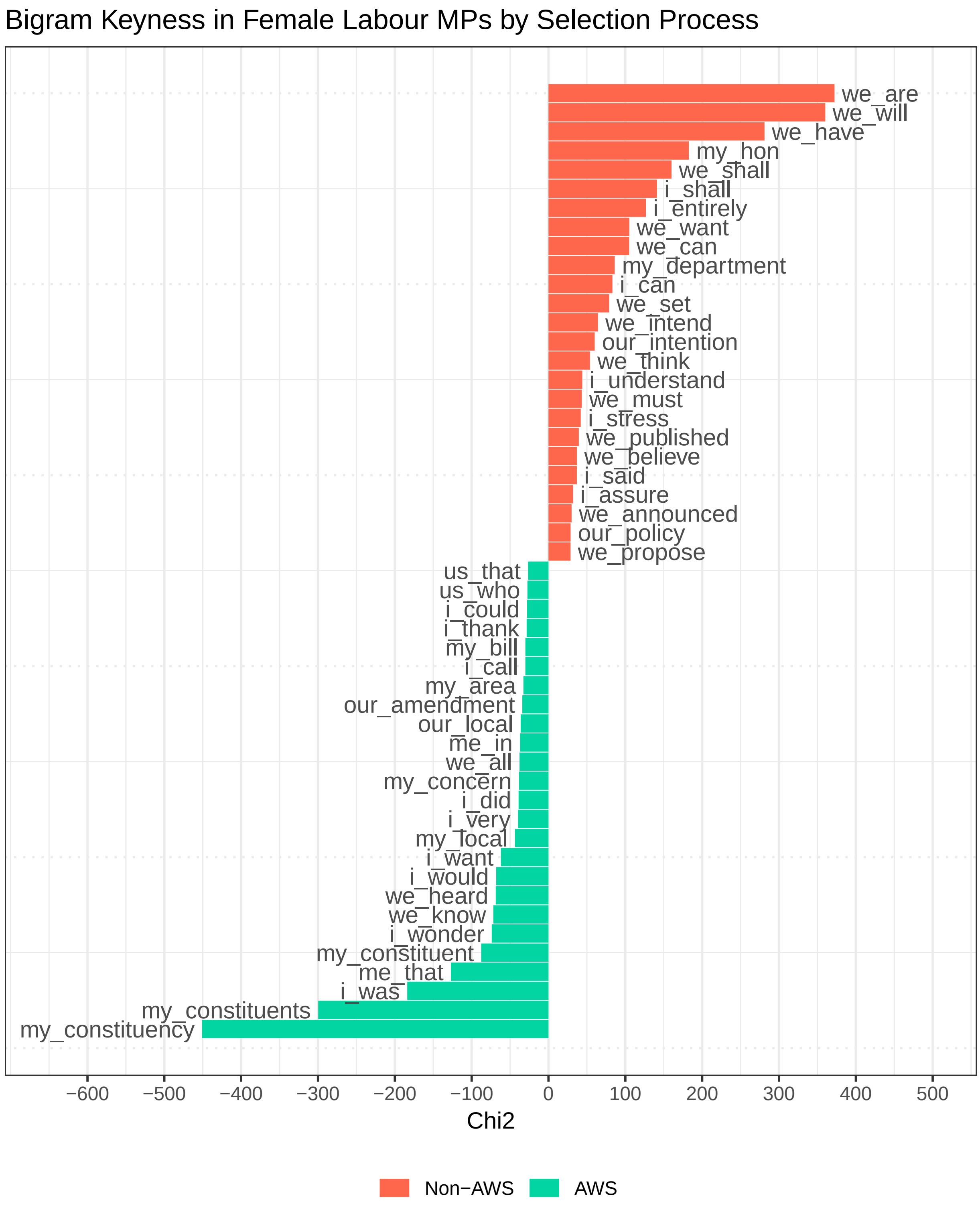
Labour vs Conservative

The keyness differences between Labour and Conservative MPs are much greater than gender differences within Labour. The very high use of “Lady” by Conservative MPs is reflective of the greater proportion of female MPs in other parties, as a Conservative



Bigrams

We created bigrams of all first person plural and singular pronouns for female Labour MPs.


Bigram Keyness in Female Labour MPs by Selection Process
we_are
we_will
we_have
my_hon
we_shall
i_shall
i_entirely
we_want
we_can
my_department
i_can
we_set
we_intend
our_intention
we_think
i_understand
we_must
i_stress
we_published
we_believe
i_said
i_assure
we_announced
our_policy
we_propose
us_that
us_who
i_could
i_thank
my_bill
i_call
my_area
our_amendment
our_local
me_in
we_all
my_concern
i_did
i_very
my_local
i_want
i_would
we_heard
we_know
i_wonder
my_constituent
me_that
i_was
my_constituents
my_constituency
−600
−500
−400
−300
−200
−100
0
100
200
300
400
500
Chi2
Non−AWS
AWS

Topic Models

Short lists vs Non-Short lists

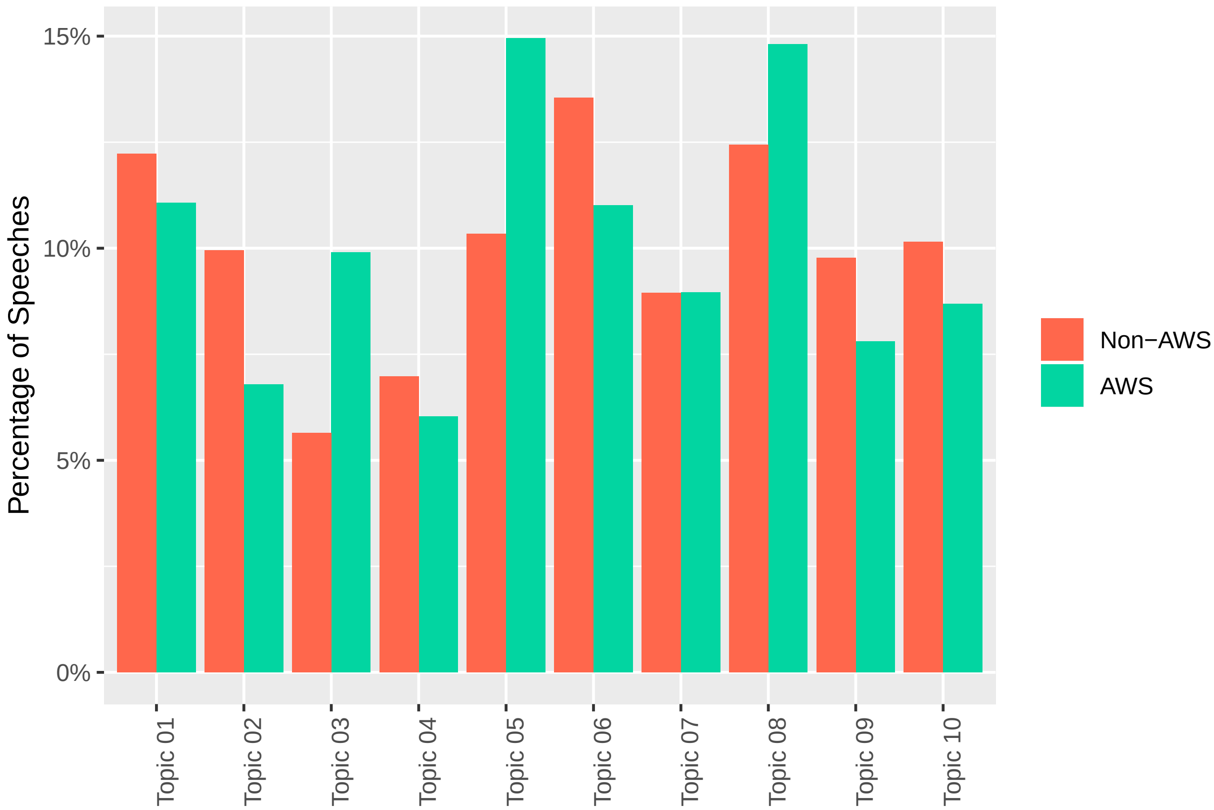


Table 9: Topic Model Terms (continued below)

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
housing	amendment	mr	women	tax
industry	clause	constituency	world	pay
energy	act	constituents	rights	million
companies	legislation	north	countries	budget
transport	amendments	west	men	benefit
investment	law	council	trade	cuts
homes	committee	east	international	families
business	legal	south	pay	money
businesses	provisions	speaker	society	credit
sector	case	thank	union	government's
services	information	deputy	life	cut
market	regulations	city	human	poverty
areas	powers	leader	labour	chancellor
london	provision	two	equality	pension
development	order	today	british	jobs
private	cases	london	women's	increase
small	authorities	week	today	income
economy	lords	day	uk	billion
uk	clear	like	family	cost
jobs	1	speech	woman	benefits

Table 11: Topic Model Distribution

Topic	Not Short List Total	Short List Total	Not Short List Percentage	Short List Percentage	Relative Occure
Topic 01	3401	5918	12.23	11.07	
Topic 02	2766	3629	9.95	6.79	
Topic 03	1569	5293	5.64	9.90	
Topic 04	1941	3226	6.98	6.03	
Topic 05	2874	7995	10.33	14.95	
Topic 06	3767	5890	13.55	11.01	
Topic 07	2488	4793	8.95	8.96	
Topic 08	3460	7918	12.44	14.81	
Topic 09	2719	4173	9.78	7.80	
Topic 10	2824	4645	10.15	8.69	

Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
committee	children	might	health	police
report	young	go	care	home
issues	education	system	services	crime
review	schools	see	nhs	justice
scotland	school	like	service	violence
national	child	good	hospital	officers
process	parents	going	patients	security
department	community	things	social	victims
consultation	training	hope	mental	eu
proposals	constituency	back	staff	forces
scottish	funding	opposition	carers	cases
commission	skills	even	treatment	uk
set	good	come	cancer	court
wales	needs	problem	disabled	european
information	children’s	fact	medical	defence
role	authorities	conservative	needs	criminal
forward	communities	different	trust	domestic
progress	teachers	party	community	serious
clear	students	something	national	foreign
future	behaviour	believe	access	case

We assigned topic models using unsupervised Latent Dirichlet Allocation (Blei, Ng, and Jordan 2003), implemented in the `topicmodels` R package (Grün and Hornik 2011). See [TABLE NUMBER?] for the ten most common words in each topic model. Topic models were trained on all speeches by female Labour MPs.

Naive Bayes classification

We trained a Naive Bayes classifier with document-frequency priors and a multinomial distribution to predict the gender of speakers when given speeches by all Labour MPs in our dataset, and the selection process when only given female Labour MPs. The accuracy of both models were roughly equivalent, 70.83% accuracy when predicting gender and 70.31% when predicting short lists. By contrast, the classifier could distinguish between Labour and Conservative speeches with 74.06% accuracy.

Discussion

There do not appear to be substantial or meaningful differences in the speaking styles or topic choices of female Labour MPs selected through all women short lists when compared to their female colleagues selected through open short lists. The few small differences between male and female Labour MPs were not replicated when comparing female Labour MPs by how they were selected.

There is more gender distinction in selected terms and topics.

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