All Women Shortlists Methodology

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).

To account for the possible effects of age, parliamentary experience and cohort, and in order to compare women selected through all women shortlists to women who were not (but theoretically had the possibility to contest all-women shortlists), speech analysis has been restricted only to Labour MPs elected during or after the 1997 General Election, and before the 2017 General Election. 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 shortlists is from the House of Commons Library (Kelly 2016). Unsuccessful General Election candidates selected through all women shortlists who were subsequently elected in a byelection are classified as having been selected on an all women shortlist.

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)
- Verbs (verb)
- Auxiliary verbs (auxverb)
- Social processes (social)
- Positive emotions (posemo)
- Negative emotions (negemo)
- Tentative words (tentat)
- Words longer than six letters (Sixltr)
- First person plural pronouns (we)
- Articles (article)
- Prepositions (preps)
- Anger words (anger)
- Swear words (swear)
- Cognitive processes (cogproc)

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

General Election	Total MPs	Total Labour MPs	Total Female Labour MPs	Newly elected MPs	Intake Women	Percentage Intake Women	Intake Shortlist	Nominated Shortlist
1997	659	418	101	177	64	36%	35	38
2001	659	412	95	38	4	11%	0	0
2005	646	355	98	40	26	65%	23	30
2010	650	258	81	64	32	50%	28	63

[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)".

General Election	Total MPs	Total Labour MPs	Total Female Labour MPs	Newly elected MPs	Intake Women	Percentage Intake Women	Intake Shortlist	Nominated Shortlist
2015	650	232	99	49	31	63%	31	77

Data in this table is from House of Commons library reports (Kelly 2016; Audickas, Hawkins, and Cracknell 2017). All women shortlists 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).

Shortlists vs Non-Shortlists

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|.

Spacy

POS Analysis

Tokenising / Keyness

The most commonly used words by both men and women would be protocol boilerplate 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-shortlist women.

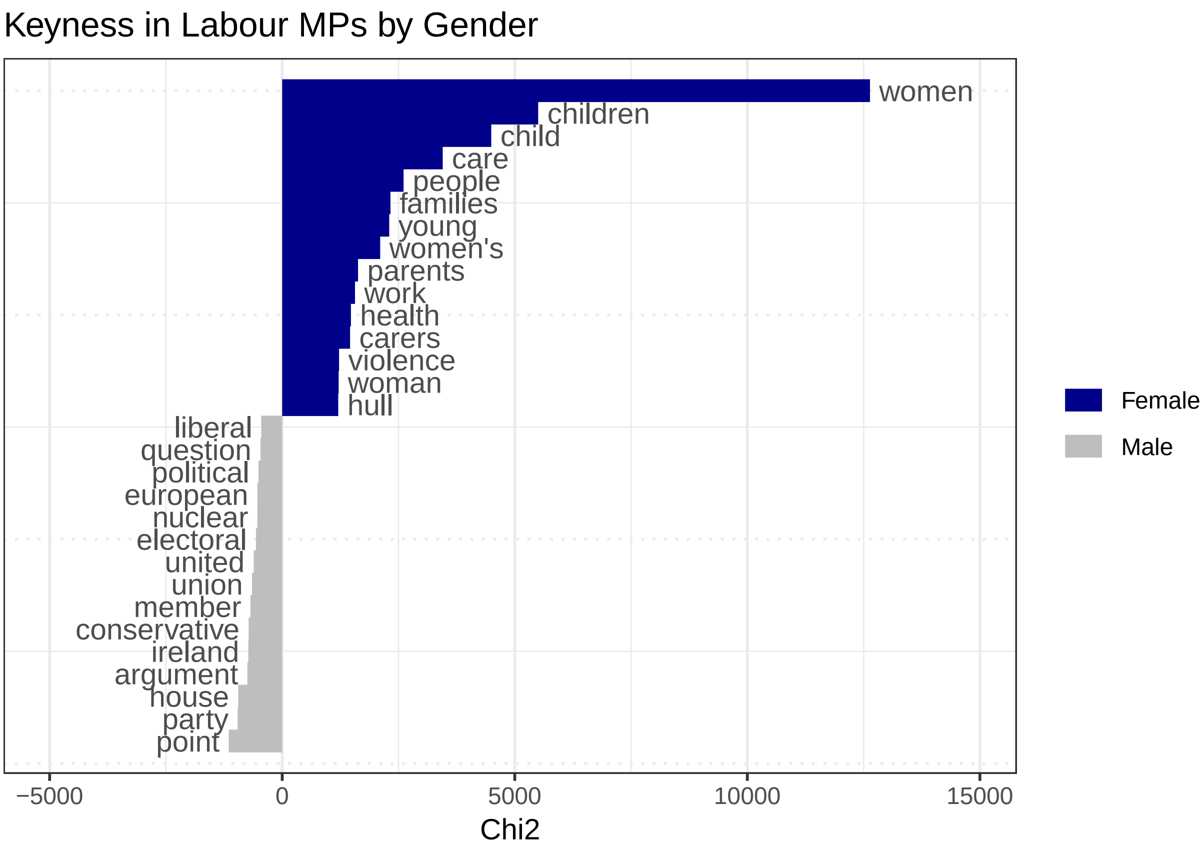
Table 2: Effect Sizes for Male and Female Labour MPs

	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	2.42	2.03	2.55	0.06	negligible
First person plural pronouns	0.97	1.42	0.99	1.51	0.01	negligible
Verbs	12.81	4.99	12.67	5.35	-0.03	negligible
Auxiliary verbs	7.90	3.45	7.93	3.69	0.01	negligible
Social processes	8.46	4.82	8.17	5.11	-0.06	negligible
Positive emotions	2.73	2.48	2.57	2.54	-0.06	negligible
Negative emotions	1.16	1.68	1.08	1.77	-0.05	negligible
Tentative words	1.48	1.74	1.57	1.90	0.05	negligible
More than six letters	19.82	6.96	19.08	7.33	-0.11	negligible
Articles	7.64	3.30	7.96	3.55	0.10	negligible
Prepositions	12.57	4.41	12.14	4.74	-0.10	negligible
Anger words	0.24	0.82	0.24	0.79	0.01	negligible
Swear words	0.00	0.06	0.00	0.09	0.01	negligible
Cognitive processes	8.68	4.82	8.82	5.14	0.03	negligible
Words per Sentence	43.23	19.41	40.79	19.74	-0.12	negligible
Total Word Count	402.34	689.78	369.53	645.77	-0.05	negligible
Flesh-Kincaid Grade Level	10.64	7.58	9.63	7.75	-0.13	negligible

Table 3: Effect Sizes for Female Labour MPs by selection process

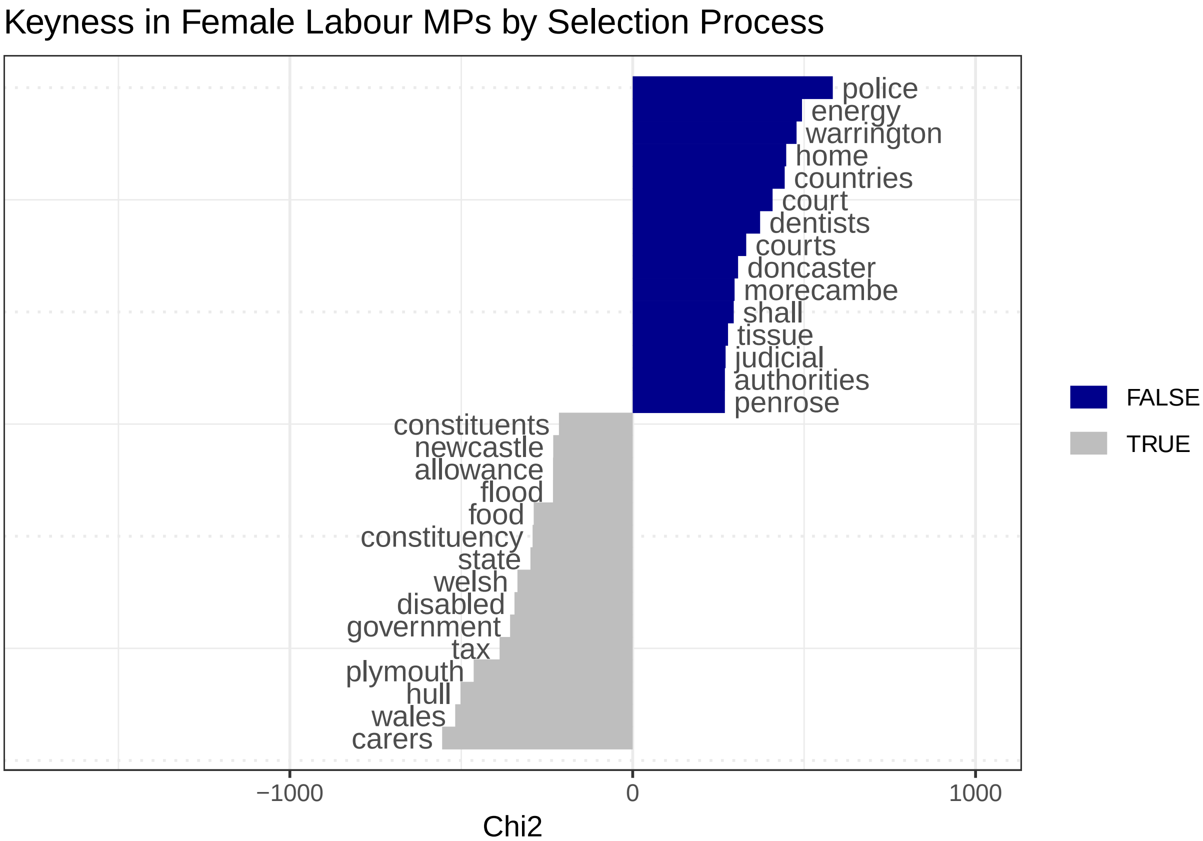
	All Women Shortlists		Open Shortlists		Effect Size	
	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Pronouns	10.01	4.66	10.18	4.47	-0.04	negligible
First person singular pronouns	1.86	2.41	1.95	2.42	-0.04	negligible
First person plural pronouns	0.88	1.36	1.15	1.51	-0.19	negligible
Verbs	12.87	5.09	12.68	4.79	0.04	negligible
Auxiliary verbs	7.93	3.48	7.85	3.38	0.02	negligible
Social processes	8.46	4.93	8.44	4.58	0.00	negligible
Positive emotions	2.69	2.52	2.81	2.42	-0.05	negligible
Negative emotions	1.17	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	19.72	7.06	20.03	6.75	-0.05	negligible
Articles	7.69	3.38	7.55	3.14	0.04	negligible
Prepositions	12.55	4.54	12.63	4.15	-0.02	negligible
Anger words	0.23	0.78	0.24	0.90	-0.01	negligible
Swear words	0.00	0.06	0.00	0.05	0.01	negligible
Cognitive processes	8.59	4.89	8.85	4.67	-0.06	negligible
Words per Sentence	43.61	20.18	42.48	17.79	0.06	negligible
Total Word Count	401.30	702.85	404.36	663.60	0.00	negligible
Flesh-Kincaid Grade Level	10.80	7.88	10.33	6.96	0.07	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.

Shortlists vs Non-Shortlists



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]. [AWS MPs given policy briefs related to these areas? Seeking them out?]

Topic Models

We assigned topic models using Latent Dirichlet Allocation (Blei, Ng, and Jordan 2003), implemented in the `topicmodels` R package (Grün and Hornik 2011). See Table 4 for the ten most common words in each topic model.

[2]Special Educational Needs

Shortlists vs Non-Shortlists

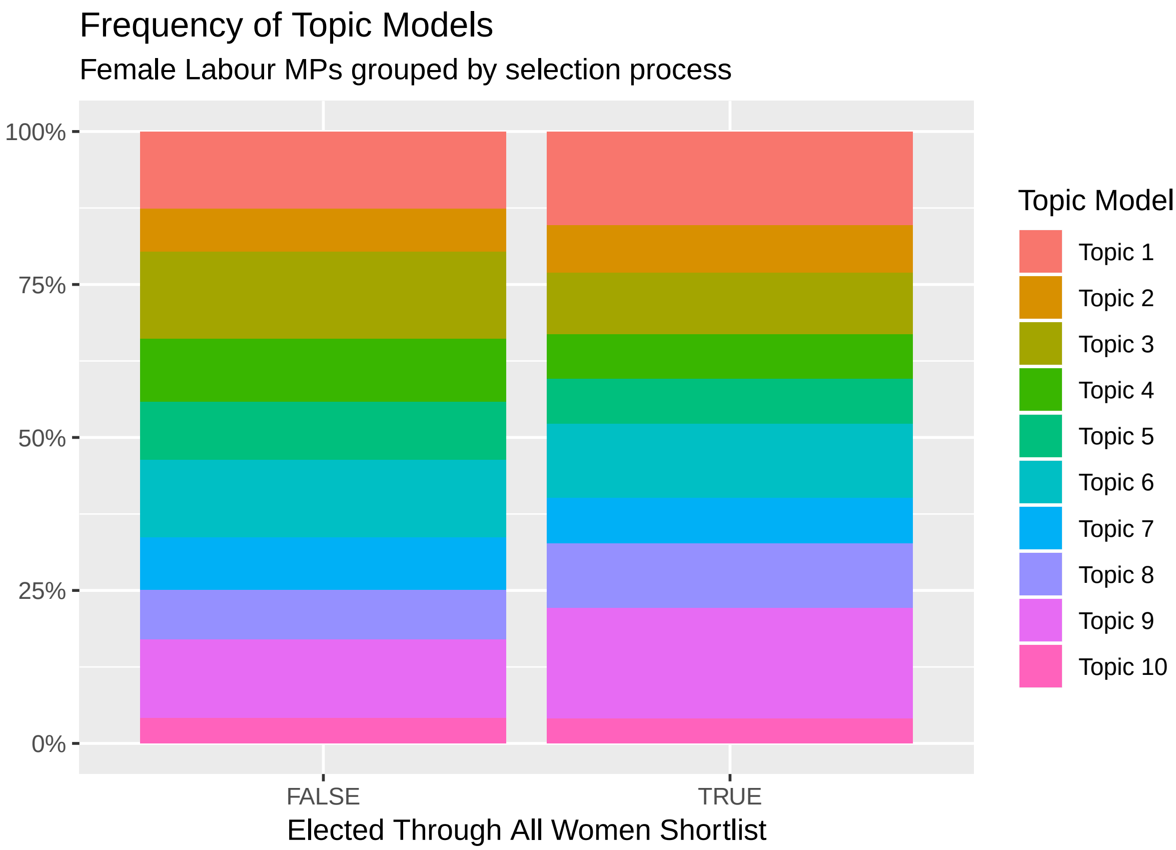


Table 4: Topic Model Terms (continued below)

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
report	children	legislation	housing	health
committee	young	clause	authorities	care
office	child	act	sector	services
question	education	amendment	scheme	nhs
mr	schools	law	homes	service
statement	school	case	services	hospital
review	parents	amendments	authority	patients
thank	families	might	council	mental
department	skills	system	planning	carers
issues	training	legal	financial	social

Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
european	women	constituency	tax	energy
world	police	london	pay	industry
countries	home	transport	million	companies
uk	crime	areas	money	wales
international	officers	city	budget	uk
party	violence	area	cuts	scotland
parliament	justice	council	benefit	scottish
british	victims	constituents	credit	market

Table 6: Topic Model Distribution

topic	topic_count	freq
Topic 1	8148	15.23%
Topic 2	4182	7.82%
Topic 3	5376	10.05%
Topic 4	3896	7.28%
Topic 5	3917	7.32%
Topic 6	6471	12.1%
Topic 7	4002	7.48%
Topic 8	5612	10.49%
Topic 9	9675	18.09%
Topic 10	2204	4.12%
Non-Short List		
Topic 1	3489	12.55%
Topic 2	1964	7.06%
Topic 3	3949	14.2%
Topic 4	2878	10.35%
Topic 5	2633	9.47%
Topic 6	3527	12.68%
Topic 7	2376	8.54%
Topic 8	2264	8.14%
Topic 9	3554	12.78%
Topic 10	1174	4.22%

Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
political	behaviour	services	cut	food
eu	men	north	jobs	amendment

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