

All Women Short lists 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 short lists to women who were not (but theoretically had the possibility to contest all-women short lists), 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 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)
- 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		Percentage Women MPs	Newly elected MPs	Intake Women	Percentage Intake Women	Intake Short list	Nominated Short list
		Labour MPs	Female Labour MPs						
1997	659	418	101	24.2%	177	64	36%	35	38
2001	659	412	95	23.1%	38	4	11%	0	0
2005	646	355	98	27.6%	40	26	65%	23	30
2010	650	258	81	31.4%	64	32	50%	28	63

¹e.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	Percentage Women MPs	Newly elected MPs	Intake Women	Percentage Intake Women	Intake Short list	Nominated Short list
2015	650	232	99	42.7%	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 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).

Short lists vs Non-Short lists

The following plots show changes in the occurrences 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 $|0.1|$.

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 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-short list 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 Short lists		Open Shorlists		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

Table 4: Part-of-Speech Effect Sizes for Male and Female Labour MPs

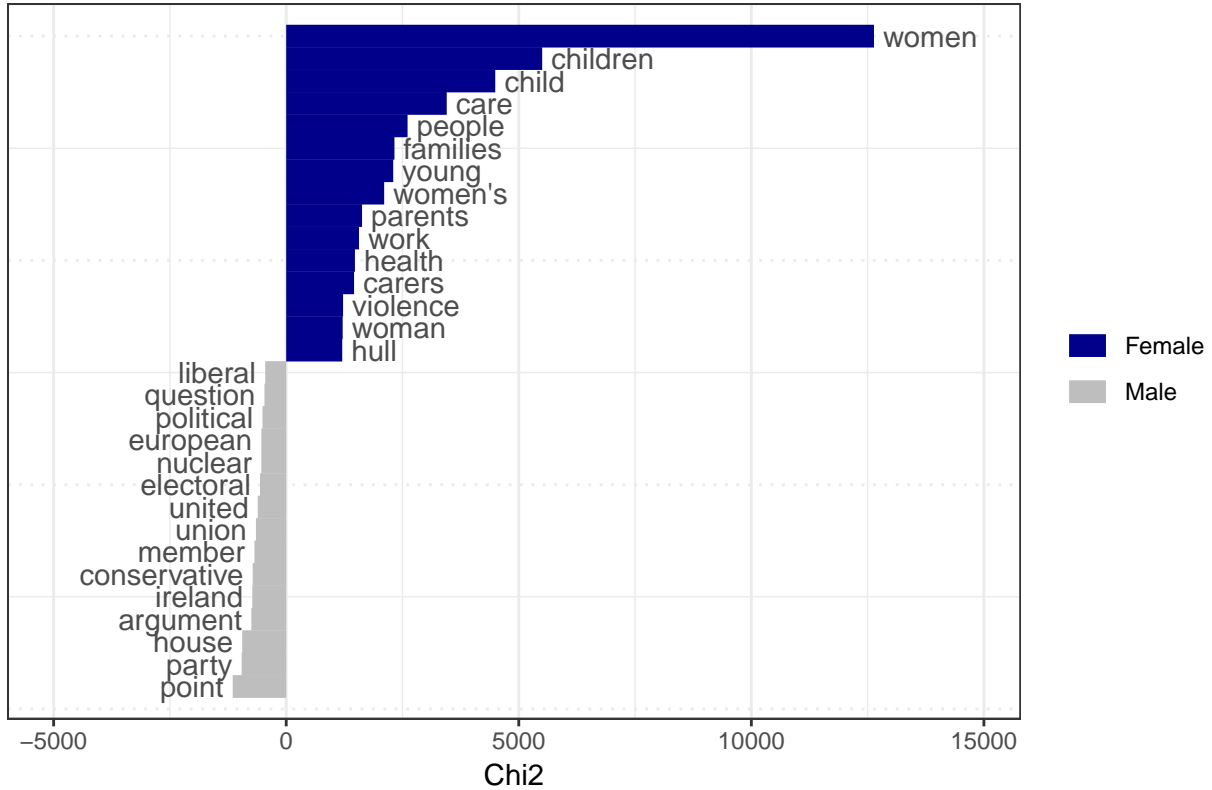
Word Type	Women		Men		Effect Size	
	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Nouns	22.23	9.59	21.72	10.95	-0.04	negligible
Plural Nouns	5.89	3.72	5.07	3.80	-0.16	negligible
Singular Nouns	15.64	9.83	16.04	11.19	0.03	negligible
Adjectives	9.58	4.77	9.29	5.29	-0.02	negligible
Adverbs	4.91	4.26	5.07	4.91	0.03	negligible
Verbs	20.95	9.52	20.80	10.27	-0.02	negligible

Table 5: Part-of-Speech Effect Sizes for Male and Female Labour MPs

Word Type	All Women Short lists		Open Shorlists		Effect Size	
	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Nouns	22.22	8.76	22.24	9.98	-0.04	negligible
Plural Nouns	6.06	3.60	5.80	3.77	-0.16	negligible
Singular Nouns	15.54	8.96	15.70	10.25	0.03	negligible
Adjectives	9.83	4.59	9.45	4.86	-0.02	negligible
Adverbs	4.95	3.77	4.89	4.48	0.03	negligible
Verbs	20.89	9.03	20.98	9.76	-0.02	negligible

Men vs Women

Keyness in Labour MPs by Gender

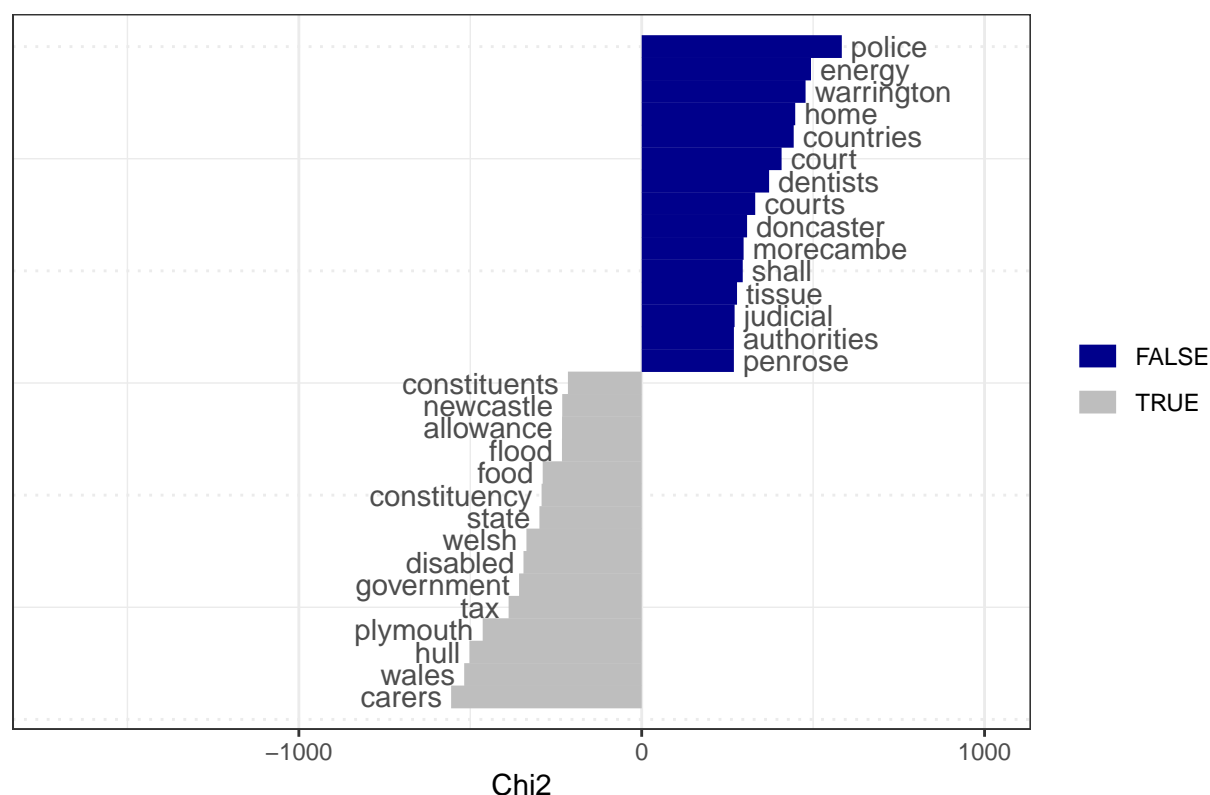


Keyness – a linguistic measure of the frequency of different words in two groups of texts – reveals clear

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 in Female Labour MPs by Selection Process



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 making more references to their “constituency” and its “constituents”

²Special Educational Needs

Topic Models

Short lists vs Non-Short lists

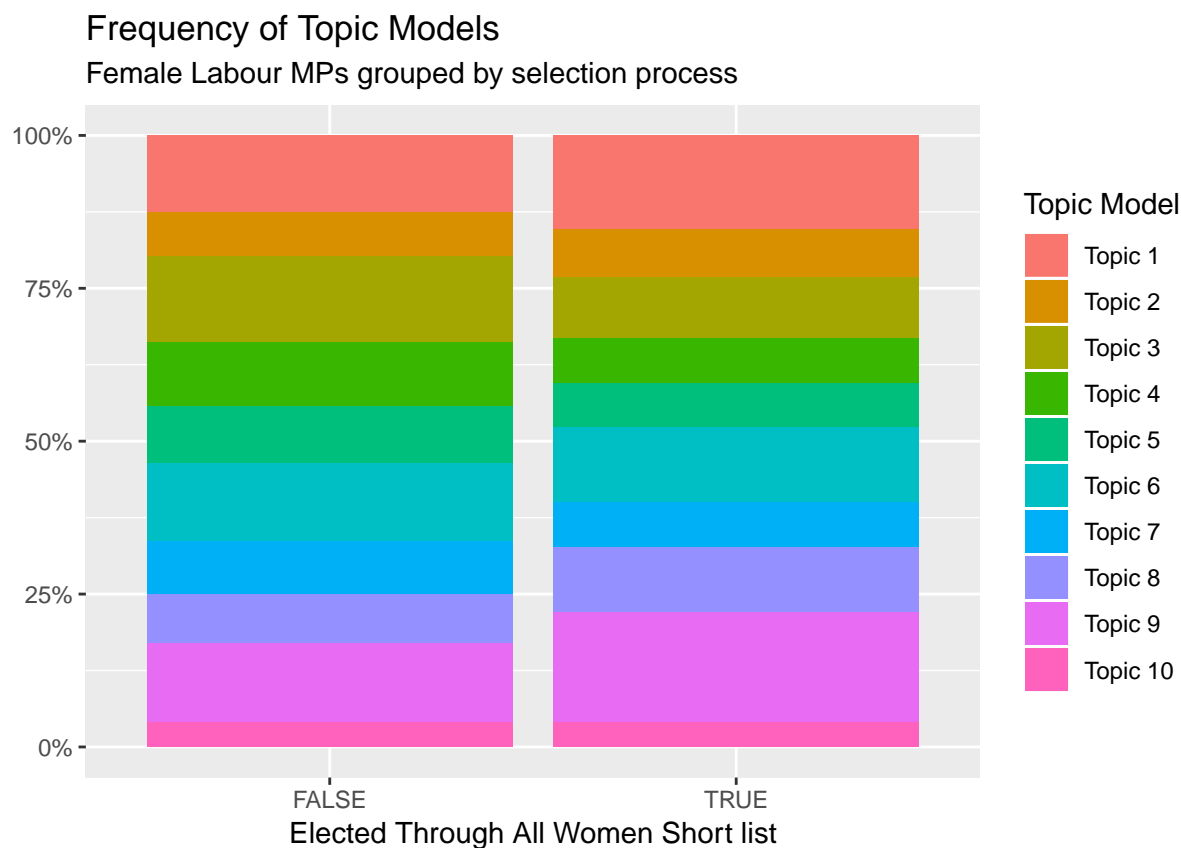


Table 6: Topic Model Terms (continued below)

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

Table 8: Topic Model Distribution

Topic	Not Short List Total	Short List Total	Not Short List Percentage	Short List Percentage
Topic 1	3489	8148	12.55	15.23
Topic 2	1964	4182	7.06	7.82
Topic 3	3949	5376	14.20	10.05
Topic 4	2878	3896	10.35	7.28
Topic 5	2633	3917	9.47	7.32
Topic 6	3527	6471	12.68	12.10
Topic 7	2376	4002	8.54	7.48
Topic 8	2264	5612	8.14	10.49
Topic 9	3554	9675	12.78	18.09
Topic 10	1174	2204	4.22	4.12

Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
parliament	justice	council	benefit	scottish
british	victims	constituents	credit	market
political	behaviour	services	cut	food
eu	men	north	jobs	amendment

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 NUMBER?] for the ten most common words in each topic model.

Non-AWS women had more speeches assigned to topic 3 (14.20% vs 10.05%), a topic that, like the gender-differences in word keyness above, refers to the parliamentary process itself. Conversely, AWS women had more speeches in topic 1 (15.23% vs 12.55%) which also includes multiple references to the parliamentary process itself.

Machine learning

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.

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. Small differences between male and female Labour MPs were not replicated when comparing female Labour MPs by how they were selected.

References

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