All Women Shortlists Methodology

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1 Descriptive Statistics

Table 1 shows the number of Labour MPs elected in each general election from 1997 to 2015, including newly elected MPs (the "intake"), the number of newly elected MPs from all women shortlists (AWS), and the number of candidates selected through all women shortlists. Data in Table 1 is from the House of Commons Library (Audickas, Hawkins, & Cracknell, 2017; Kelly & White, 2016). All women shortlists were not used by Labour during the 2001 General Election.

Table 1: Labour MPs and Intakes

General Election	Total MPs	Labour MPs	Female Labour MPs	Labour MPs Intake	Intake Women	Intake Shortlist	Nominated Shortlist
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 shows the total size of the dataset in speeches and words by each party, including by gender for each party, and in the case of female Labour MPs, by AWS status. Details on inclusion criteria are given below.

Table 2: Number of Speeches and Words in Dataset

Gender	Speeches	Words
All	657,547	239,123,685
Female	149,805	56,589,501
Male	507,742	182,534,184
Conservatives		
All	285,308	96,186,824
Female	48,771	15,779,116
Male	236,537	80,407,708
Labour		
All	262,000	99,986,437
Female	84,615	34,159,304
Non-All Women Shortlists	28,653	11,623,184
All Women Shortlists	55,962	22,536,120
Male	177,385	65,827,133
Liberal Democrat		
All	72,719	28,947,968
Female	7,552	3,232,822
Male	65,167	25,715,146
Other		
All	37,520	14,002,456
Female	8,867	3,418,259
Male	28,653	10,584,197

2 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 (Bligh, Merolla, Schroedel, & Gonzalez, 2010; Jones, 2016). 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 shortlists. We examined differences in speaking styles using the `Linguistic Inquiry and Word Count 2015` (LIWC) dictionary (Pennebaker, Boyd, Jordan, & Blackburn, 2015) and the `spaCy` (Honnibal & 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 trained a Naive Bayes classifier to distinguish AWS and non-AWS speeches. We used structured topic models (STM) to identify the topics discussed by AWS and non-AWS MPs.

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 who theoretically had the opportunity to contest all-women shortlists), 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 data on MPs' gender and party affiliation are from a previously assembled dataset (Odell, 2018). Information on candidates selected through all women shortlists is from the House of Commons Library (Kelly & White, 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, regardless of the selection process for that byelection. Speeches made by MPs while suspended from the Labour party where classified the same as if they had not been suspended. The dataset includes 408 different Labour MPs, 167 female MPs, 119 elected from All Women Shortlists and 48 elected from open shortlists, along with 241 male MPs.

3 Results

3.1 Linguistic Inquiry and Word Count

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, and calculations for determining grade level (Kincaid, Fishburne, Rogers, & Chissom, 1975) were produced using `stringi` (Gagolewski, 2018), an `R` wrapper to the ICU regex library.

Following research by Yu (2014) and Newman, Groom, Handelman, & Pennebaker (2008) on gender differences in language, we focused on the following LIWC categories to compare MPs' speeches:

- 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)

[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)".

- Prepositions (preps)
- Anger words (anger)
- Swear words (swear)
- Cognitive processes (cogproc)
- 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 the `Quanteda` (Benoit, 2018) and `stringi` (Gagolewski, 2018) `R` packages.

3.1.1 Women vs Men

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	0.98	1.42	0.99	1.51	0.01	negligible
Verbs	12.82	5.00	12.67	5.35	-0.03	negligible
Auxiliary verbs	7.91	3.45	7.93	3.69	0.01	negligible
Social processes	8.46	4.81	8.16	5.11	-0.06	negligible
Positive emotions	2.73	2.49	2.57	2.54	-0.06	negligible
Negative emotions	1.15	1.69	1.07	1.78	-0.05	negligible
Tentative words	1.48	1.74	1.58	1.90	0.05	negligible
More than six letters	10.62	3.67	10.26	3.92	-0.10	negligible
Articles	7.64	3.30	7.96	3.55	0.09	negligible
Prepositions	12.58	4.41	12.14	4.73	-0.10	negligible
Anger words	0.23	0.83	0.24	0.79	0.01	negligible
Swear words	0.00	0.06	0.00	0.09	0.01	negligible
Cognitive processes	8.68	4.83	8.82	5.15	0.03	negligible
Words per Sentence	43.99	19.92	41.43	20.30	-0.13	negligible
Total Word Count	402.72	691.10	370.13	647.25	-0.05	negligible
Flesh-Kincaid Grade Level	10.97	7.77	9.91	7.96	-0.13	negligible

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

3.1.2 Shortlists vs Non-Shortlists

Figure 1 shows 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, as measured since the time an MP was first elected. There do not appear to be any notable changes in speaking style over the course of female Labour MPs' careers. Figure 2 shows changes in the occurrences of the same selected terms from 1997–2017. As in Figure 1, there do not appear to be any meaningful trends in the use of the selected terms over time.

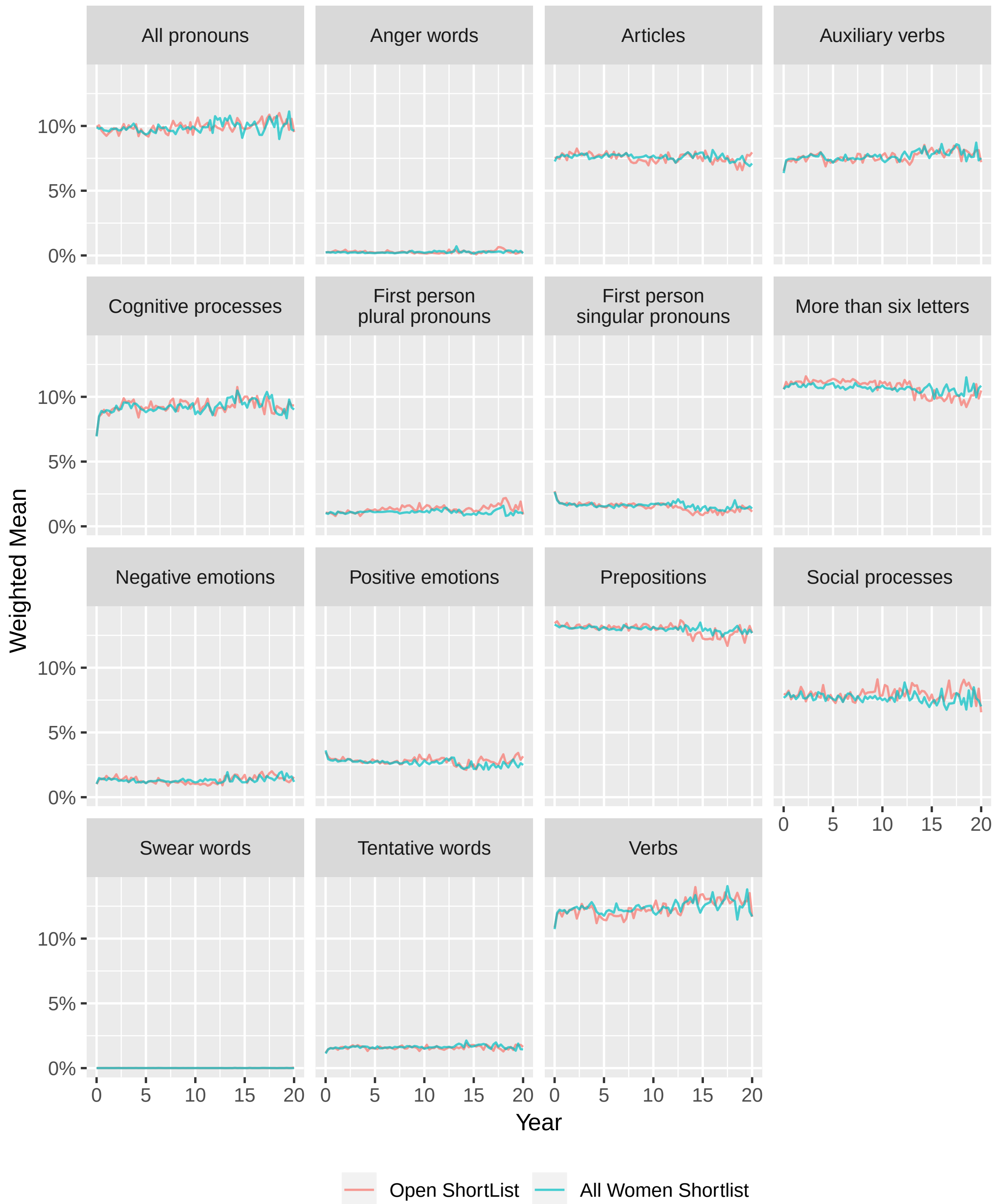

Figure 1: Occurrence of selected LIWC terms, by time as MP

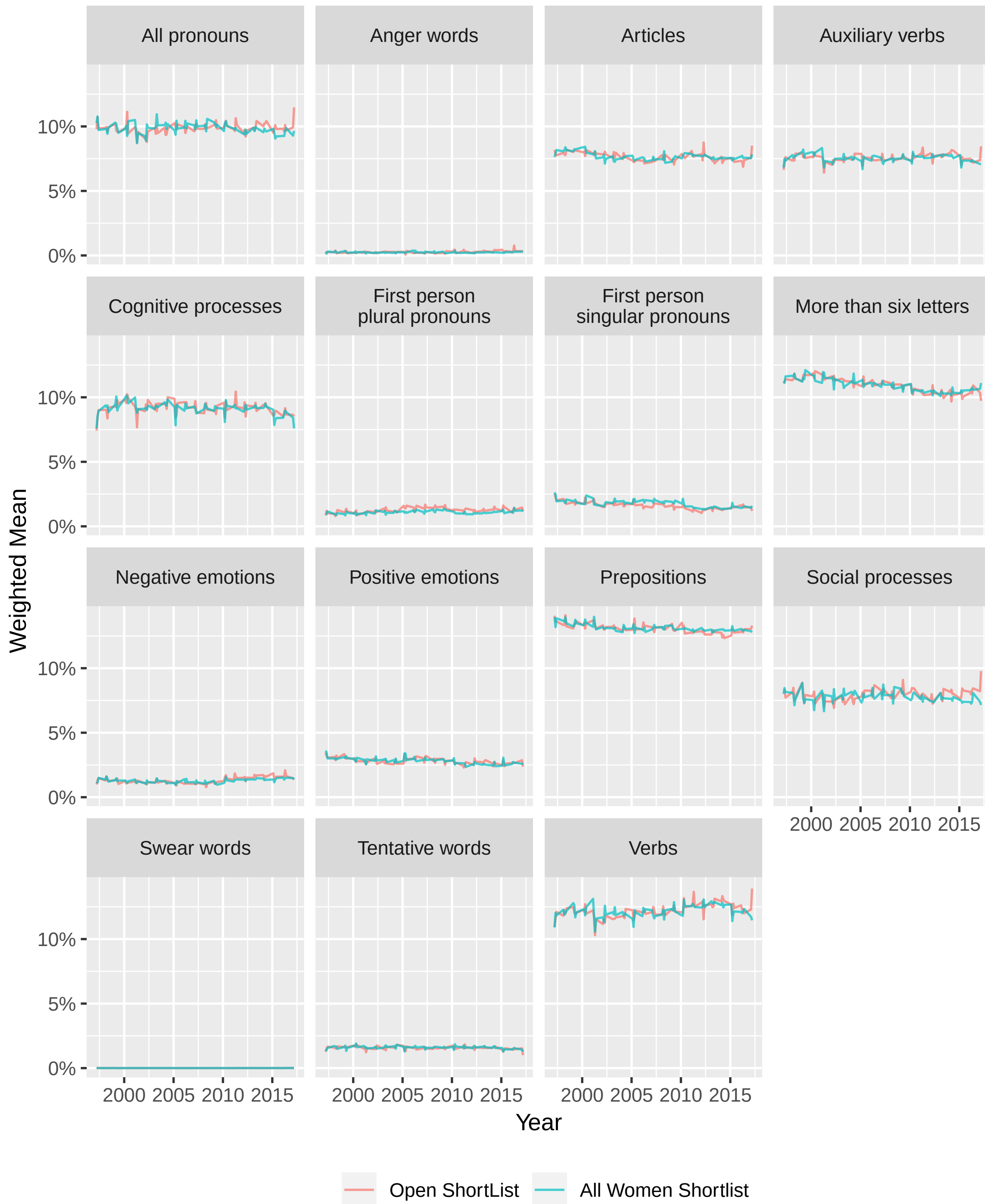

Figure 2: Occurrence of selected LIWC terms, by date

Table 4: 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	10.19	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	1.16	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	8.46	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	1.68	0.02	negligible
Tentative words	1.48	1.75	1.49	1.73	0.00	negligible
More than six letters	10.56	3.72	10.74	3.56	-0.05	negligible
Articles	7.69	3.38	7.55	3.14	0.04	negligible
Prepositions	12.55	4.54	12.63	4.14	-0.02	negligible
Anger words	0.23	0.79	0.24	0.91	-0.01	negligible
Swear words	0.00	0.06	0.00	0.05	0.01	negligible
Cognitive processes	8.59	4.90	8.85	4.69	-0.05	negligible
Words per Sentence	44.39	20.69	43.21	18.31	0.06	negligible
Total Word Count	401.70	704.15	404.73	664.87	0.00	negligible
Flesh-Kincaid Grade Level	11.13	8.06	10.64	7.15	0.07	negligible

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|.

3.1.3 Conservatives vs Labour

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	10.61	4.84	0.10	negligible
First person singular pronouns	1.98	2.51	2.14	2.56	0.06	negligible
First person plural pronouns	0.98	1.48	1.22	1.70	0.15	negligible
Verbs	12.72	5.24	12.92	5.14	0.04	negligible
Auxiliary verbs	7.93	3.61	8.16	3.58	0.06	negligible
Social processes	8.26	5.02	8.11	4.80	-0.03	negligible
Positive emotions	2.63	2.52	2.85	2.66	0.09	negligible
Negative emotions	1.10	1.75	1.04	1.79	-0.03	negligible
Tentative words	1.55	1.85	1.57	1.88	0.01	negligible
More than six letters	10.38	3.84	10.31	3.75	-0.02	negligible
Articles	7.86	3.47	7.81	3.45	-0.01	negligible
Prepositions	12.28	4.63	12.35	4.49	0.02	negligible
Anger words	0.24	0.80	0.24	0.82	0.00	negligible
Swear words	0.00	0.08	0.00	0.10	0.00	negligible
Cognitive processes	8.77	5.05	8.85	5.06	0.01	negligible
Words per Sentence	42.26	20.22	43.07	20.39	0.04	negligible
Total Word Count	380.64	661.91	336.23	594.06	-0.07	negligible
Flesh-Kincaid Grade Level	10.25	7.91	10.54	7.99	0.04	negligible

There are no categories with effect sizes exceeding |0.2| between Labour and Conservative MPs, and only one (first person plural pronouns) exceeding |0.1|.

3.1.4 All MPs Gender Differences

There are no categories with effect sizes exceeding |0.2| when comparing all male and female MPs elected from 1997 onwards. There is only one category, "Articles", with an effect size of 0.11, greater than the |0.1| threshold suggested by Newman et al. (2008).

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	12.89	4.98	12.80	5.26	-0.02	negligible
Auxiliary verbs	8.01	3.45	8.08	3.64	0.02	negligible
Social processes	8.44	4.77	7.99	4.92	-0.09	negligible
Positive emotions	2.84	2.53	2.70	2.58	-0.06	negligible
Negative emotions	1.10	1.65	1.07	1.78	-0.01	negligible
Tentative words	1.47	1.73	1.61	1.91	0.08	negligible
More than six letters	10.57	3.66	10.34	3.83	-0.06	negligible
Articles	7.63	3.30	8.00	3.51	0.11	negligible
Prepositions	12.59	4.36	12.22	4.61	-0.08	negligible
Anger words	0.23	0.79	0.25	0.82	0.02	negligible
Swear words	0.00	0.05	0.00	0.10	0.01	negligible
Cognitive processes	8.68	4.80	8.93	5.12	0.05	negligible
Words per Sentence	44.00	20.02	42.69	20.65	-0.07	negligible
Total Word Count	376.81	648.62	358.56	624.84	-0.03	negligible
Flesh-Kincaid Grade Level	10.95	7.82	10.43	8.08	-0.07	negligible

3.2 POS Analysis

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	22.17	9.56	21.67	10.92	-0.05	negligible
Plural Nouns	5.86	3.71	5.04	3.79	-0.22	small
Singular Nouns	15.61	9.81	16.01	11.16	0.04	negligible
Adjectives	9.58	4.77	9.28	5.29	-0.06	negligible
Adverbs	4.91	4.25	5.06	4.91	0.04	negligible
Verbs	20.97	9.52	20.81	10.28	-0.02	negligible

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

	All Women Shortlists		Open Shorlists		Effect Size	
Word Type	Mean	SD	Mean	SD	Cohen's d	Magnitude
All Nouns	22.16	8.72	22.18	9.97	-0.04	negligible
Plural Nouns	6.03	3.59	5.77	3.76	-0.16	negligible
Singular Nouns	15.50	8.93	15.67	10.23	0.03	negligible
Adjectives	9.83	4.58	9.45	4.86	-0.02	negligible
Adverbs	4.95	3.76	4.89	4.49	0.03	negligible
Verbs	20.92	9.02	21.00	9.77	-0.02	negligible

Part-of-speech (POS) tagging was done using the `spaCy` library (Honnibal & Montani, 2017) and the `spacyr` package (Benoit & Matsuo, 2018). There is one small gender difference (d = -0.22) in the use of plural nouns, which make up 5.86% of the words used by female Labour MPs, compared to 5.04% of words spoken by male Labour MPs. As with LIWC, there are no categories where $d >= |0.2|$ when comparing female Labour MPs by selection process, and only one category – plural nouns – with an effect size of $d >= |0.1|$.

3.3 Keyness

We calculated the keyness of words to identify gender differences in the choices of topics raised and terminology used by both male and female Labour MPs, and by short-list and non-shortlist female Labour MPs. We have also calculated keyness between Labour and Conservative MPs for the purposes of illustration. All keyness figures include the 25 most disproportionately common words among each group, as determined by χ^2 tests using `quanteda` (Benoit, 2018).

3.3.1 Labour 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, illustrated in Figure 3.

Unsurprisingly, despite male MPs saying almost twice as many words (65,827,133 vs 34,159,304) 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 use "women's" and "woman" in parliamentary debate. 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 Labour MPs are more comfortable using the traditional language of House of Commons debate, and are more concerned with the rules, procedures and processes of the parliamentary system than their female colleagues.

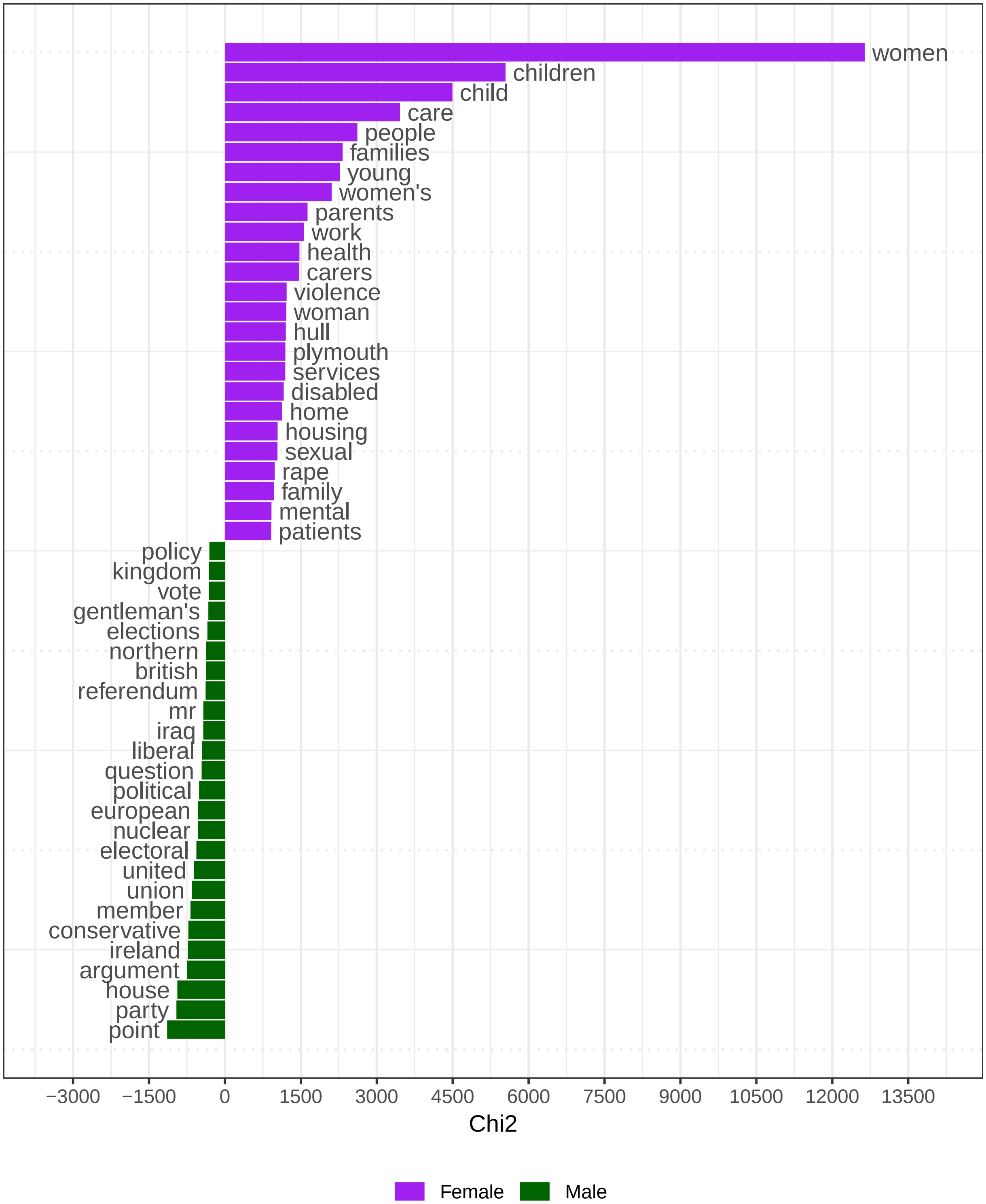

Figure 3: Keyness between Labour MPs, by Gender

3.3.2 Shortlists vs Non-Shortlists

Keyness differences by selection process (Figure 4) are not as obviously stereotypical. Nonetheless, the most common words amongst AWS MPs included “carers”, “disabled”, “bedroom” and “sen” (Special Educational

Needs). Also of note is AWS MPs making more references to their "constituency" and its "constituents", suggesting that AWS MPs may draw more heavily on the fact they were elected by their constituents as a source political legitimacy, or are more likely to illustrate a point with an example from their constitutency, compared to non-AWS MPs.

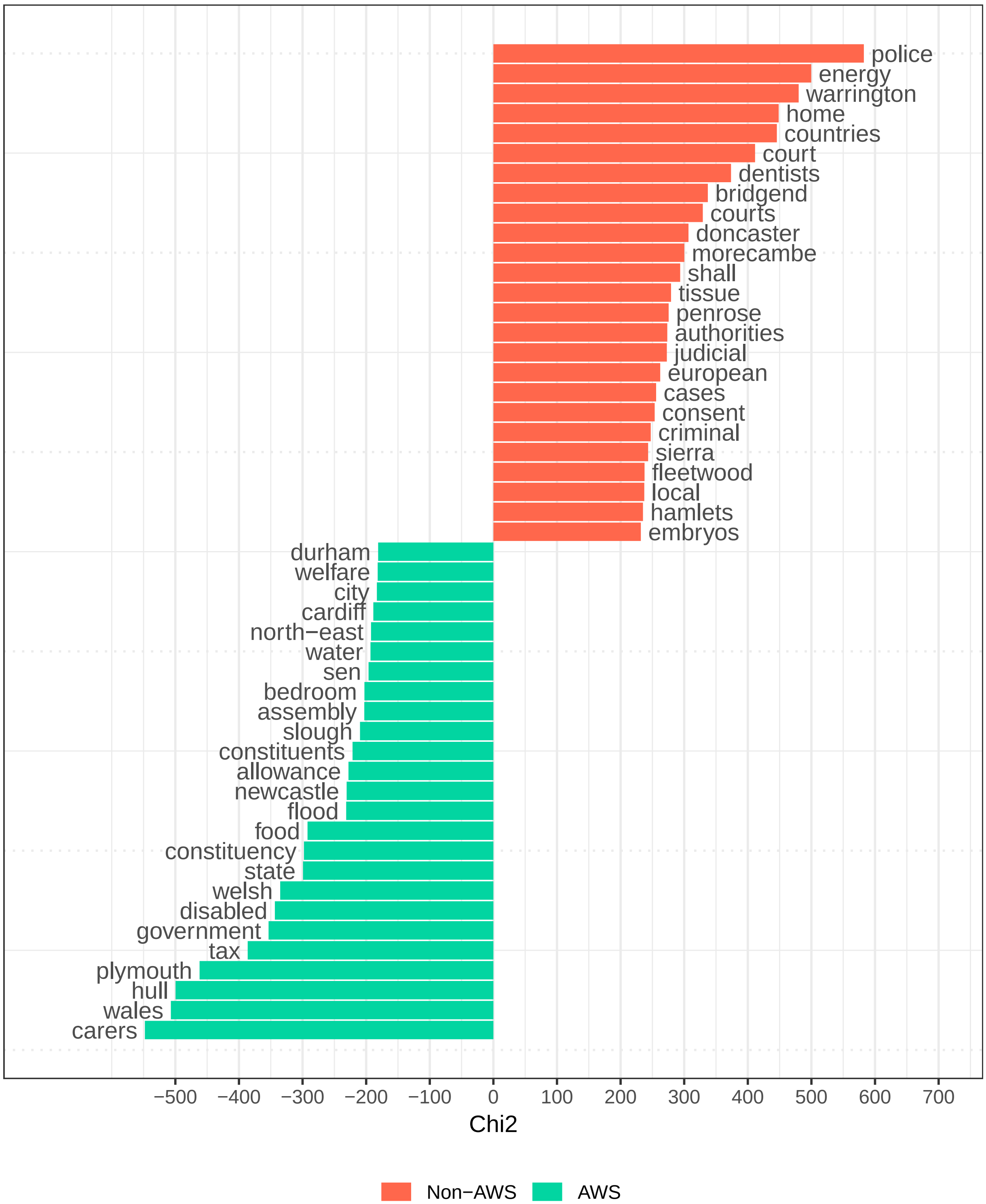

Figure 4: Keyness between Female Labour MPs, by Selection Process

3.3.3 Labour vs Conservative

The keyness differences (Figure 5) between Labour and Conservative MPs are much greater than gender or AWS 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 it is often used to refer to comments by other members of the house. It may also represent a greater use of traditional house decorum by Conservative MPs.

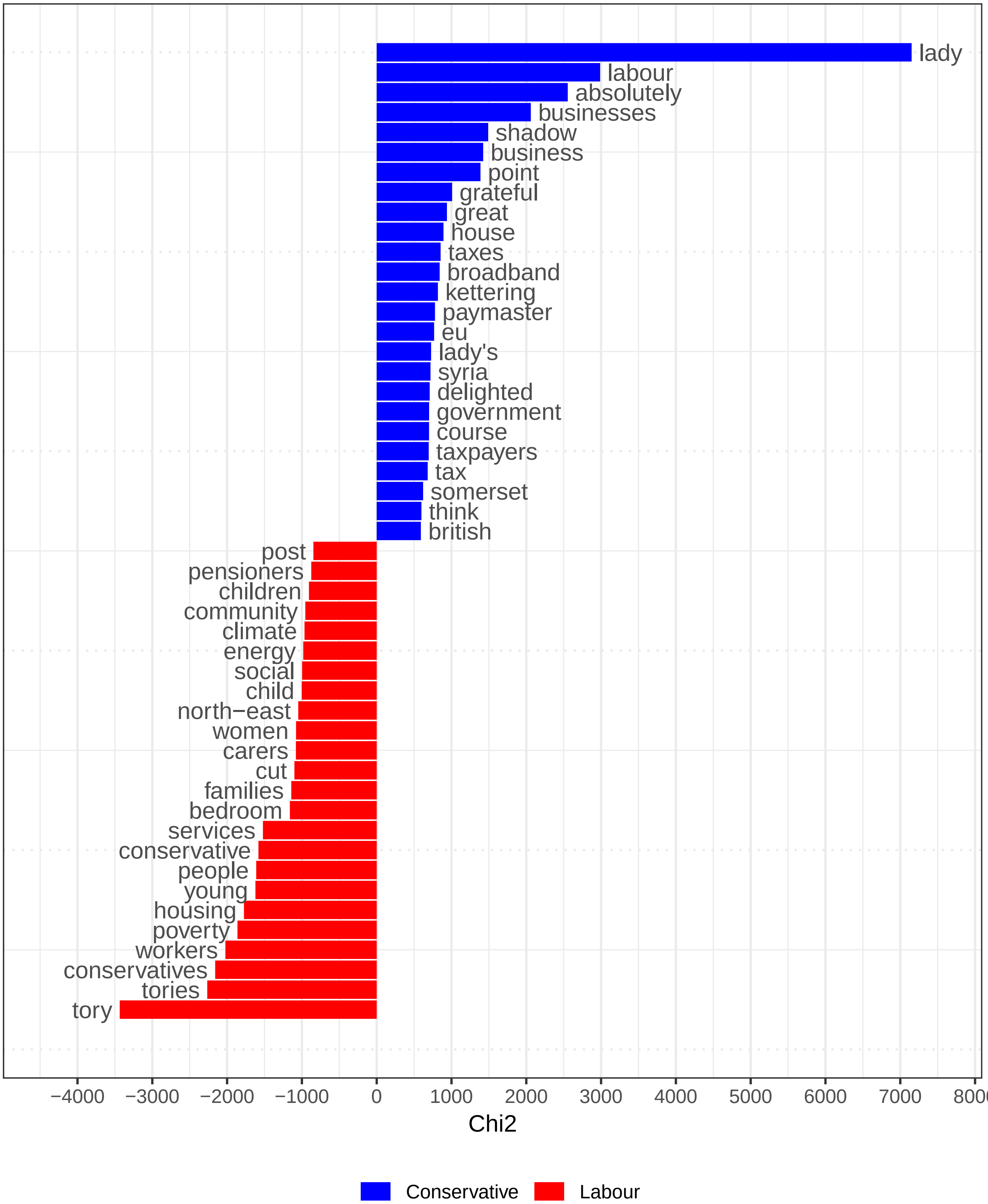

Figure 5: Keyness between Labour and Conservative MPs

3.4 Bigrams

We created bigrams of all first person plural and singular pronouns for female Labour MPs (Figure 6). As above, AWS MPs are far more likely to make references to their constituency or their constituents, and the use of bigrams confirms these references are to their specific constituency/constituents, rather than those of other MPs, or constituencies in general.

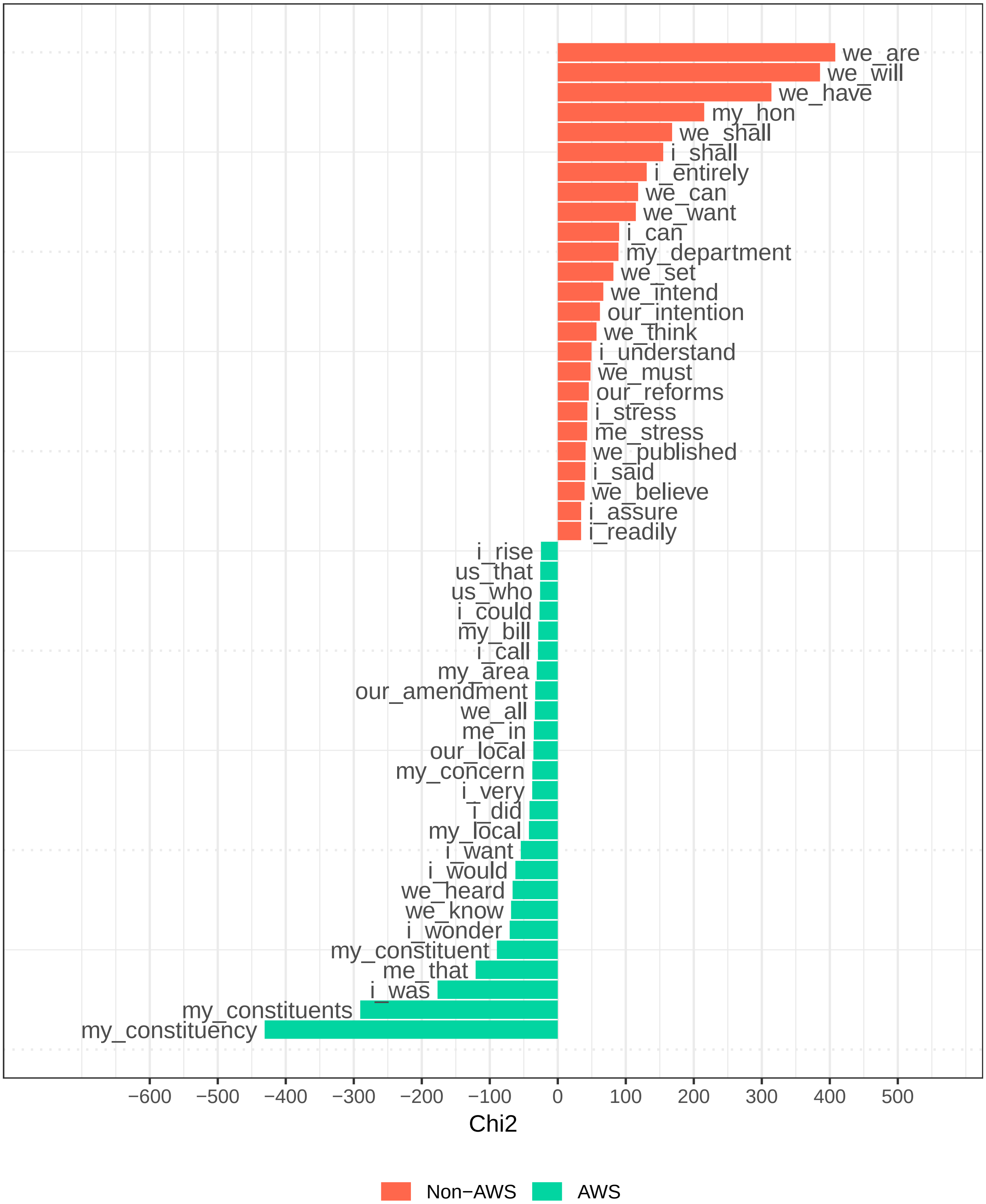

Figure 6: Bigram Keyness in Female Labour MPs by Selection Process

3.5 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, 70.67% accuracy when predicting gender and 71.22% when predicting shortlists. By contrast, the classifier could distinguish between Labour and Conservative speeches with 74.23% accuracy.

3.6 Topic Models

Using topic models to classify text is widely used in social sciences (Grimmer & Stewart, 2013), as, when combined with the large volume of plain text data available, it allows for a rapid and consistent method of analysis . Topic modelling and other statistic methods of textual analysis are not a substitute for reading the texts themselves, but can augment other analysis or – as in this case – analyse and classify larger amounts of text than would be feasible using human coders (Grimmer & Stewart, 2013). Topic models classify a series of documents (in this case individual speeches) into one of a given number of topics, identifying terms that are common in some documents but rare in others. When developing topic models, there is a trade-off between high precision in the classification of each document with broader topics when using smaller numbers of topics, or lower precision in individual speech classification with more finely-grained topics when using larger numbers of topics. Grimmer & Stewart (2013) also highlight the importance of validating unsurpervised topic models when applied to new sets of texts, which we have done below.

The R package `stm` (Roberts, Stewart, & Tingley, 2018) implements a structured topic model (STM) (Arora et al., 2013; Roberts, Stewart, & Airoldi, 2016). An STM incorporates covariates into the topic classification algorithm, creating possibilities for hypothesis testing. This differs from traditional topic modelling methods using latent variables to identify topics (e.g. with latent Dirichlet allocation Blei, Ng, & Jordan, 2003), and then comparing proportions of each topic to one or more external variables. STM allows us to incorporate the variables we are interested in to the topic model itself using a generalised linear model; i.e. the proportion of speechs classified as belonging to each topic can vary as a function of the AWS and gender variables.

We incorporated the AWS status of speakers and their gender as prevalence covariates into our topic model.

We created six topic models with different numbers of topics (K). We created models with 30, 45, 60, 80 and 100 topics, and used a topic selection algorithm developed by Lee & Mimno (2014), implemented in the `stm` package (Roberts et al., 2018), which resulted in $K = 66$. Figure 7 shows, clockwise from the top-left, the exclusivity score, held out likelihood with 50% of documents held out, the multinomial dispersion of the STM residuals (Taddy, 2012), semantic coherence (Mimno, Wallach, Talley, Leenders, & McCallum, 2011), and the lower bound of each topic model.

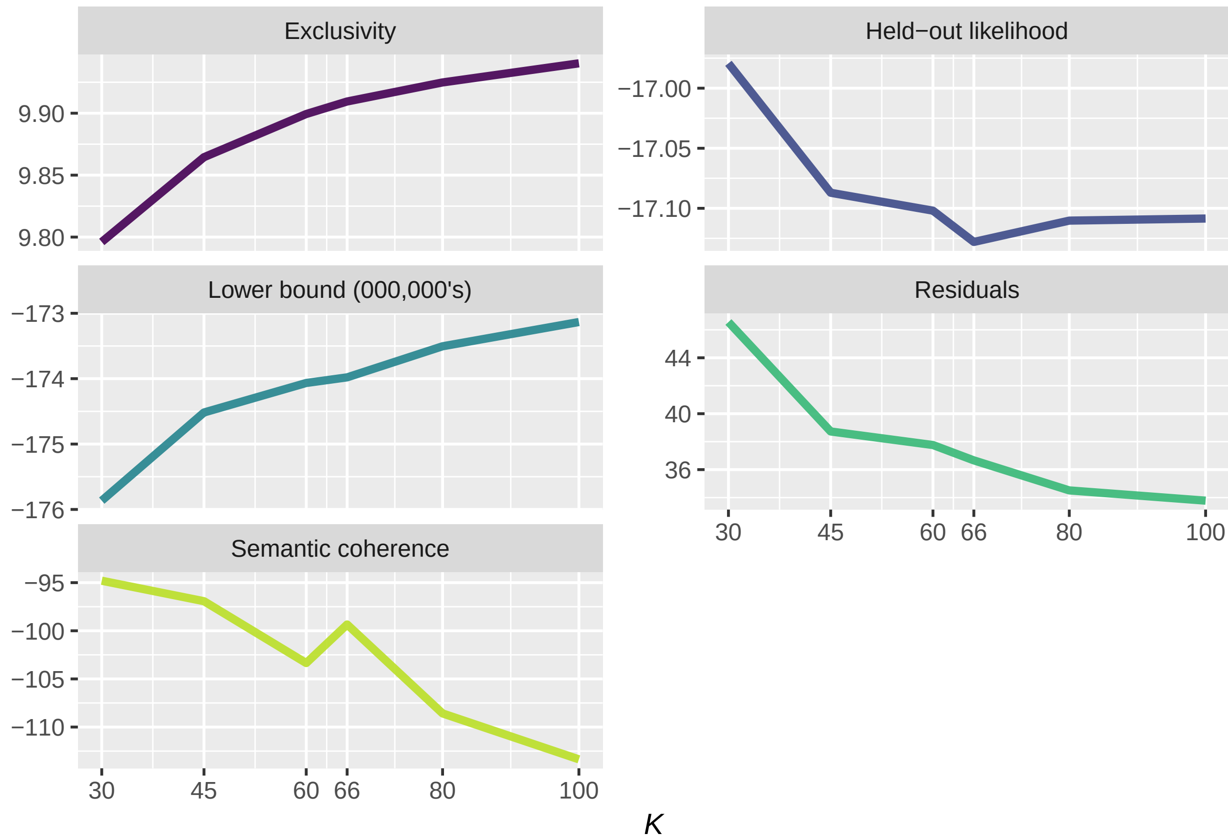

Figure 7: Topic Model Selection

As seen in Figure 7, the $K = 66$ result appears to produce the best result, a topic model with 66 topics, across 251,072 speeches with a dictionary of 241,625 words. All models were created using the "spectral" method developed by Arora et al. (2013), implemented in the `stm` package by Roberts et al. (2018).

Figure 8 is a Fruchterman-Reingold force-directed diagram (Fruchterman & Reingold, 1991) of correlations between different topics. Larger vertices indicate more common topics (amongst both male and female Labour MPs), and the colour scale indicates the proportion of speeches classed in that topic made by AWS and non-AWS female Labour MPs, respectively. Edges indicate positive correlations between the two linked topics.

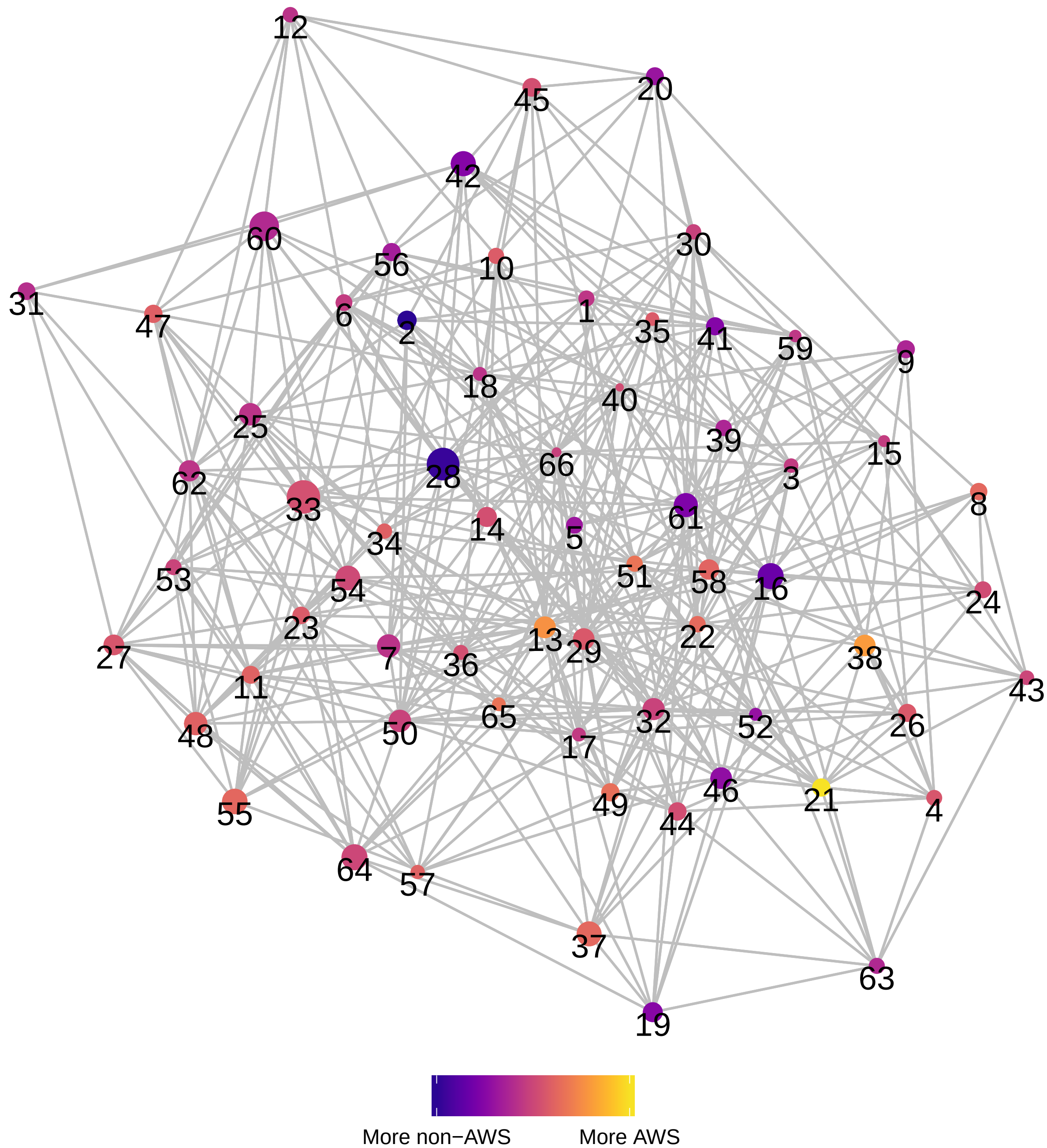

Figure 8: Fruchterman-Reingold plot of Topic Network

The `stm` package includes the `estimateEffect` function, which creates a regression model (Table 9) using individual documents (speeches) as observations, with the proportion of a each document fitting each topic as the dependent variable and model covariates (AWS status and gender) as independent variables. The intercept in this model is all speeches by male Labour MPs.

Table 9: Topic Estimates

	Estimate	Standard Error	t value	Pr(>|t|)
Topic 1 – Employment & unions				

Table 9: Topic Estimates *(continued)*

	Estimate	Standard Error	t value	Pr(>|t|)
Intercept	0.0120862	0.0001184	102.0514999	< 0.001 ***
Non-AWS	-0.0003799	0.0003228	-1.1766212	0.24
AWS	-0.0013394	0.0002463	-5.4389520	< 0.001 ***
Topic 2 – Legal system				
Intercept	0.0167032	0.0001793	93.1606154	< 0.001 ***
Non-AWS	0.0069690	0.0005410	12.8821364	< 0.001 ***
AWS	-0.0033040	0.0003299	-10.0153800	< 0.001 ***
Topic 3 – Roads				
Intercept	0.0116638	0.0001505	77.4900594	< 0.001 ***
Non-AWS	-0.0014892	0.0004117	-3.6174617	< 0.001 ***
AWS	-0.0019496	0.0002949	-6.6116237	< 0.001 ***
Topic 4 – Housing				
Intercept	0.0112839	0.0001700	66.3580229	< 0.001 ***
Non-AWS	0.0044549	0.0004888	9.1138451	< 0.001 ***
AWS	0.0060414	0.0003719	16.2452789	< 0.001 ***
Topic 5 – Police, firefighters & prison				
Intercept	0.0140713	0.0001765	79.7077064	< 0.001 ***
Non-AWS	0.0032607	0.0005310	6.1405587	< 0.001 ***
AWS	-0.0003205	0.0003598	-0.8906177	0.37
Topic 6 – Northern Ireland				
Intercept	0.0089512	0.0000476	188.1040345	< 0.001 ***
Non-AWS	0.0000912	0.0001259	0.7243872	0.47
AWS	-0.0003743	0.0001139	-3.2875592	0.001 **
Topic 7 – Committee				
Intercept	0.0213277	0.0001401	152.2393713	< 0.001 ***
Non-AWS	-0.0007069	0.0003793	-1.8634845	0.062
AWS	-0.0019503	0.0002692	-7.2457231	< 0.001 ***
Topic 8 – Schools				
Intercept	0.0147218	0.0001996	73.7524738	< 0.001 ***
Non-AWS	-0.0009633	0.0005047	-1.9086784	0.056
AWS	0.0021242	0.0004257	4.9894237	< 0.001 ***
Topic 9 – Energy & climate change				
Intercept	0.0170582	0.0001996	85.4566489	< 0.001 ***
Non-AWS	-0.0011694	0.0005192	-2.2524645	0.024 *
AWS	-0.0035142	0.0004352	-8.0751172	< 0.001 ***
Topic 10 – Defence				
Intercept	0.0157860	0.0001938	81.4435774	< 0.001 ***
Non-AWS	-0.0075456	0.0004654	-16.2134656	< 0.001 ***
AWS	-0.0054174	0.0003678	-14.7292498	< 0.001 ***
Topic 11 – Parliament				
Intercept	0.0118988	0.0000785	151.5356984	< 0.001 ***
Non-AWS	-0.0036960	0.0002025	-18.2504201	< 0.001 ***
AWS	-0.0010972	0.0001535	-7.1492967	< 0.001 ***
Topic 12 – International politics				
Intercept	0.0126072	0.0001309	96.3364797	< 0.001 ***
Non-AWS	-0.0042348	0.0003192	-13.2669303	< 0.001 ***
AWS	-0.0054787	0.0002561	-21.3901700	< 0.001 ***

Table 9: Topic Estimates *(continued)*

	Estimate	Standard Error	t value	Pr(>|t|)
Topic 13 – Ministers				
Intercept	0.0167416	0.0001104	151.6885875	< 0.001 ***
Non-AWS	-0.0029753	0.0002833	-10.5039388	< 0.001 ***
AWS	0.0031499	0.0002370	13.2901248	< 0.001 ***
Topic 14 – Policy impact				
Intercept	0.0115296	0.0000460	250.5201444	< 0.001 ***
Non-AWS	0.0002501	0.0001402	1.7838929	0.074
AWS	0.0013692	0.0001041	13.1500213	< 0.001 ***
Topic 15 – Gender				
Intercept	0.0048725	0.0001184	41.1676413	< 0.001 ***
Non-AWS	0.0123752	0.0003738	33.1029141	< 0.001 ***
AWS	0.0119884	0.0003415	35.1095704	< 0.001 ***
Topic 16 – Regional development				
Intercept	0.0230411	0.0001283	179.5583409	< 0.001 ***
Non-AWS	0.0070435	0.0003614	19.4874058	< 0.001 ***
AWS	0.0002605	0.0002557	1.0188203	0.31
Topic 17 – Communications				
Intercept	0.0097585	0.0001199	81.4042658	< 0.001 ***
Non-AWS	-0.0006802	0.0003543	-1.9200223	0.055
AWS	-0.0012008	0.0002623	-4.5784156	< 0.001 ***
Topic 18 – Immigration				
Intercept	0.0087077	0.0000961	90.5799857	< 0.001 ***
Non-AWS	0.0007341	0.0002708	2.7113024	0.007 **
AWS	-0.0004178	0.0001887	-2.2136439	0.027 *
Topic 19 – Health system				
Intercept	0.0161572	0.0002158	74.8710588	< 0.001 ***
Non-AWS	0.0112570	0.0006451	17.4495585	< 0.001 ***
AWS	0.0062992	0.0004682	13.4533589	< 0.001 ***
Topic 20 – International development				
Intercept	0.0160712	0.0001998	80.4544519	< 0.001 ***
Non-AWS	0.0004256	0.0005224	0.8147287	0.42
AWS	-0.0033515	0.0003870	-8.6602597	< 0.001 ***
Topic 21 – Benefits & disability				
Intercept	0.0120341	0.0001418	84.8889126	< 0.001 ***
Non-AWS	0.0009239	0.0003845	2.4028394	0.016 *
AWS	0.0120278	0.0003165	37.9965526	< 0.001 ***
Topic 22 – Sport & culture				
Intercept	0.0127175	0.0001618	78.6004689	< 0.001 ***
Non-AWS	-0.0024666	0.0004094	-6.0242852	< 0.001 ***
AWS	0.0007466	0.0003289	2.2696559	0.023 *
Topic 23 – History				
Intercept	0.0137416	0.0001065	129.0349444	< 0.001 ***
Non-AWS	-0.0060877	0.0002707	-22.4908633	< 0.001 ***
AWS	-0.0040068	0.0002038	-19.6633448	< 0.001 ***
Topic 24 – Higher education & skills				
Intercept	0.0143130	0.0001657	86.3994893	< 0.001 ***
Non-AWS	-0.0010222	0.0004387	-2.3299284	0.020 *

Table 9: Topic Estimates *(continued)*

	Estimate	Standard Error	t value	Pr(>|t|)
AWS	-0.0001155	0.0003378	-0.3418543	0.73
Topic 25 – Concurring point				
Intercept	0.0155249	0.0000455	340.8643243	< 0.001 ***
Non-AWS	-0.0018970	0.0001204	-15.7591726	< 0.001 ***
AWS	-0.0030025	0.0000881	-34.0898947	< 0.001 ***
Topic 26 – Pensions				
Intercept	0.0146921	0.0001656	88.7061087	< 0.001 ***
Non-AWS	0.0007088	0.0004266	1.6614446	0.097
AWS	0.0026239	0.0003306	7.9358847	< 0.001 ***
Topic 27 – Points of order				
Intercept	0.0177825	0.0001312	135.5164893	< 0.001 ***
Non-AWS	-0.0065270	0.0003204	-20.3722927	< 0.001 ***
AWS	-0.0048112	0.0002530	-19.0151971	< 0.001 ***
Topic 28 – Issues				
Intercept	0.0344884	0.0000992	347.7808680	< 0.001 ***
Non-AWS	0.0070252	0.0002815	24.9548904	< 0.001 ***
AWS	-0.0025891	0.0001988	-13.0261303	< 0.001 ***
Topic 29 – Constituencies				
Intercept	0.0131813	0.0000489	269.7079872	< 0.001 ***
Non-AWS	0.0011059	0.0001440	7.6807265	< 0.001 ***
AWS	0.0029681	0.0001078	27.5384439	< 0.001 ***
Topic 30 – Ethnic groups & racism				
Intercept	0.0085768	0.0000759	113.0279104	< 0.001 ***
Non-AWS	0.0019119	0.0002180	8.7682209	< 0.001 ***
AWS	0.0019284	0.0001703	11.3231174	< 0.001 ***
Topic 31 – Amendments				
Intercept	0.0149882	0.0001575	95.1836747	< 0.001 ***
Non-AWS	-0.0017636	0.0004298	-4.1035700	< 0.001 ***
AWS	-0.0033144	0.0003282	-10.0985521	< 0.001 ***
Topic 32 – Reports				
Intercept	0.0169549	0.0001064	159.3397451	< 0.001 ***
Non-AWS	0.0012137	0.0002922	4.1538908	< 0.001 ***
AWS	0.0013410	0.0002357	5.6894508	< 0.001 ***
Topic 33 – People				
Intercept	0.0377531	0.0001138	331.6403748	< 0.001 ***
Non-AWS	-0.0022831	0.0002859	-7.9846749	< 0.001 ***
AWS	-0.0010462	0.0002441	-4.2855238	< 0.001 ***
Topic 34 – Wales & Scotland				
Intercept	0.0135400	0.0001613	83.9505531	< 0.001 ***
Non-AWS	-0.0047679	0.0003714	-12.8373417	< 0.001 ***
AWS	-0.0023185	0.0003053	-7.5932499	< 0.001 ***
Topic 35 – Alcohol & tobacco				
Intercept	0.0108964	0.0001606	67.8441920	< 0.001 ***
Non-AWS	-0.0008338	0.0004299	-1.9396388	0.052
AWS	0.0011983	0.0003138	3.8193041	< 0.001 ***
Topic 36 – Place names				
Intercept	0.0083690	0.0000676	123.7103735	< 0.001 ***

Table 9: Topic Estimates *(continued)*

	Estimate	Standard Error	t value	Pr(>|t|)
Non-AWS	0.0000216	0.0001854	0.1164329	0.91
AWS	0.0011689	0.0001439	8.1255803	< 0.001 ***
Topic 37 – Budget				
Intercept	0.0246573	0.0001698	145.1771858	< 0.001 ***
Non-AWS	-0.0023164	0.0004581	-5.0570503	< 0.001 ***
AWS	0.0007141	0.0003659	1.9518902	0.051
Topic 38 – Tax				
Intercept	0.0193483	0.0001813	106.7409141	< 0.001 ***
Non-AWS	-0.0013548	0.0005218	-2.5962669	0.009 **
AWS	0.0054422	0.0003783	14.3865019	< 0.001 ***
Topic 39 – Private companies				
Intercept	0.0123819	0.0001248	99.2533292	< 0.001 ***
Non-AWS	0.0005534	0.0003533	1.5666914	0.12
AWS	-0.0018003	0.0002481	-7.2565512	< 0.001 ***
Topic 40 – Environment & fishing				
Intercept	0.0094616	0.0001525	62.0389897	< 0.001 ***
Non-AWS	-0.0031014	0.0003574	-8.6766592	< 0.001 ***
AWS	-0.0021450	0.0002959	-7.2480571	< 0.001 ***
Topic 41 – Crime				
Intercept	0.0141431	0.0001677	84.3317735	< 0.001 ***
Non-AWS	0.0086019	0.0005406	15.9126521	< 0.001 ***
AWS	0.0034662	0.0003583	9.6741306	< 0.001 ***
Topic 42 – Bills				
Intercept	0.0244474	0.0001473	165.9430659	< 0.001 ***
Non-AWS	0.0021314	0.0004092	5.2087163	< 0.001 ***
AWS	-0.0029693	0.0002791	-10.6387333	< 0.001 ***
Topic 43 – Children				
Intercept	0.0076744	0.0001331	57.6710441	< 0.001 ***
Non-AWS	0.0092062	0.0004013	22.9397861	< 0.001 ***
AWS	0.0095694	0.0002847	33.6152819	< 0.001 ***
Topic 44 – Utilities & PFI				
Intercept	0.0123349	0.0000949	130.0192965	< 0.001 ***
Non-AWS	-0.0007792	0.0002348	-3.3180194	< 0.001 ***
AWS	0.0002424	0.0001874	1.2930126	0.20
Topic 45 – Middle East				
Intercept	0.0174954	0.0002047	85.4622512	< 0.001 ***
Non-AWS	-0.0028459	0.0005239	-5.4327115	< 0.001 ***
AWS	-0.0017174	0.0004254	-4.0366447	< 0.001 ***
Topic 46 – Local authorities				
Intercept	0.0179705	0.0001441	124.7140327	< 0.001 ***
Non-AWS	0.0044460	0.0004071	10.9222685	< 0.001 ***
AWS	0.0001175	0.0003132	0.3752453	0.71
Topic 47 – Elections				
Intercept	0.0181739	0.0001770	102.6990229	< 0.001 ***
Non-AWS	-0.0091578	0.0004206	-21.7748190	< 0.001 ***
AWS	-0.0068048	0.0003441	-19.7752340	< 0.001 ***
Topic 48 – Debate				

Table 9: Topic Estimates *(continued)*

	Estimate	Standard Error	t value	Pr(>|t|)
Intercept	0.0180055	0.0000744	242.1652775	< 0.001 ***
Non-AWS	-0.0034976	0.0002004	-17.4542734	< 0.001 ***
AWS	-0.0009784	0.0001449	-6.7535198	< 0.001 ***
Topic 49 – Transport				
Intercept	0.0164420	0.0001989	82.6554691	< 0.001 ***
Non-AWS	-0.0027373	0.0005170	-5.2949484	< 0.001 ***
AWS	0.0008817	0.0003929	2.2442760	0.025 *
Topic 50 – Questions				
Intercept	0.0161734	0.0000751	215.2147452	< 0.001 ***
Non-AWS	0.0001342	0.0001892	0.7091762	0.48
AWS	0.0002145	0.0001590	1.3487738	0.18
Topic 51 – Families				
Intercept	0.0101048	0.0001120	90.2329097	< 0.001 ***
Non-AWS	0.0019115	0.0003350	5.7063441	< 0.001 ***
AWS	0.0058736	0.0002492	23.5724036	< 0.001 ***
Topic 52 – Health research				
Intercept	0.0088039	0.0001515	58.0975570	< 0.001 ***
Non-AWS	0.0076307	0.0004391	17.3765585	< 0.001 ***
AWS	0.0036093	0.0003241	11.1360045	< 0.001 ***
Topic 53 – Dispatch box				
Intercept	0.0075509	0.0000222	339.5595793	< 0.001 ***
Non-AWS	-0.0011340	0.0000541	-20.9643113	< 0.001 ***
AWS	-0.0009568	0.0000449	-21.2874906	< 0.001 ***
Topic 54 – Parties				
Intercept	0.0248198	0.0001254	197.9714514	< 0.001 ***
Non-AWS	-0.0066223	0.0003402	-19.4685926	< 0.001 ***
AWS	-0.0060013	0.0002642	-22.7136997	< 0.001 ***
Topic 55 – Statements				
Intercept	0.0211136	0.0000691	305.6748570	< 0.001 ***
Non-AWS	-0.0045069	0.0001825	-24.6888834	< 0.001 ***
AWS	-0.0014969	0.0001322	-11.3235789	< 0.001 ***
Topic 56 – European Union				
Intercept	0.0163497	0.0001622	100.7685715	< 0.001 ***
Non-AWS	-0.0024147	0.0004613	-5.2346807	< 0.001 ***
AWS	-0.0053902	0.0003339	-16.1442216	< 0.001 ***
Topic 57 – Locations				
Intercept	0.0100655	0.0001093	92.0882958	< 0.001 ***
Non-AWS	-0.0025098	0.0002662	-9.4300170	< 0.001 ***
AWS	0.0000362	0.0002079	0.1739532	0.86
Topic 58 – Jobs & manufacturing				
Intercept	0.0175808	0.0001699	103.5079359	< 0.001 ***
Non-AWS	-0.0016172	0.0004389	-3.6845577	< 0.001 ***
AWS	0.0012164	0.0003493	3.4822434	< 0.001 ***
Topic 59 – Small business				
Intercept	0.0070661	0.0000727	97.2469297	< 0.001 ***
Non-AWS	0.0005518	0.0001980	2.7872106	0.005 **
AWS	-0.0003661	0.0001477	-2.4786832	0.013 *

Table 9: Topic Estimates *(continued)*

	Estimate	Standard Error	t value	Pr(>|t|)
Topic 60 – Agreement & disagreement				
Intercept	0.0328535	0.0001167	281.6339411	< 0.001 ***
Non-AWS	-0.0089898	0.0003000	-29.9708198	< 0.001 ***
AWS	-0.0109420	0.0002069	-52.8929433	< 0.001 ***
Topic 61 – Voluntary sector				
Intercept	0.0187146	0.0001254	149.2922884	< 0.001 ***
Non-AWS	0.0111175	0.0003750	29.6443690	< 0.001 ***
AWS	0.0056545	0.0002501	22.6080984	< 0.001 ***
Topic 62 – Comments				
Intercept	0.0152723	0.0000672	227.1040587	< 0.001 ***
Non-AWS	-0.0029204	0.0001703	-17.1477213	< 0.001 ***
AWS	-0.0040206	0.0001217	-33.0261801	< 0.001 ***
Topic 63 – Social care				
Intercept	0.0090477	0.0001161	77.9622405	< 0.001 ***
Non-AWS	0.0094855	0.0003807	24.9132885	< 0.001 ***
AWS	0.0073834	0.0002806	26.3138604	< 0.001 ***
Topic 64 – Time				
Intercept	0.0213815	0.0000677	315.7329637	< 0.001 ***
Non-AWS	-0.0020748	0.0001766	-11.7516924	< 0.001 ***
AWS	-0.0016508	0.0001430	-11.5468764	< 0.001 ***
Topic 65 – Media & animals				
Intercept	0.0121377	0.0001639	74.0746788	< 0.001 ***
Non-AWS	-0.0057058	0.0004023	-14.1823871	< 0.001 ***
AWS	-0.0017740	0.0003206	-5.5328038	< 0.001 ***
Topic 66 – Other				
Intercept	0.0038248	0.0000114	334.2824056	< 0.001 ***
Non-AWS	0.0002529	0.0000296	8.5582161	< 0.001 ***
AWS	0.0003065	0.0000251	12.2093927	< 0.001 ***

Table 10 shows the number and percentage of speeches assigned to each topic, based on its θ value. The results in this table differ slightly from those in Table 9, as it uses a "winner-take-all" method to assign an overall topic to each speech, rather than a prevalence of a given topic across all speeches. One of the topics – Topic 66 – is never the most likely topic in the matrix of number of documents by number of topics – labelled θ by Roberts et al. (2018) – and so while it is included in the model, assignment of single topics to speeches uses the highest θ for each speech. Other topics are rarely used – Topic 53, which we labelled "Dispatch Box", only has five topics assigned to it, four from Male MPs and one from an AWS MP.

Table 10: Count and Distribution of Topics

Topic	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
(1) Employment & unions	452	0.84%	260	0.93%	2,149	1.27%
(2) Legal system	865	1.61%	1,096	3.93%	3,884	2.29%
(3) Roads	558	1.04%	298	1.07%	2,142	1.26%
(4) Housing	1,383	2.57%	665	2.39%	2,416	1.43%

Table 10: Count and Distribution of Topics *(continued)*

Topic	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
(5) Police, firefighters & prison	1,046	1.94%	709	2.54%	3,353	1.98%
(6) Northern Ireland	221	0.41%	66	0.24%	603	0.36%
(7) Committee	1,050	1.95%	492	1.77%	3,888	2.29%
(8) Schools	1,367	2.54%	522	1.87%	3,780	2.23%
(9) Energy & climate change	1,105	2.05%	745	2.67%	4,630	2.73%
(10) Defence	794	1.48%	280	1.00%	3,999	2.36%
(11) Parliament	375	0.70%	85	0.31%	1,079	0.64%
(12) International politics	289	0.54%	161	0.58%	2,021	1.19%
(13) Ministers	872	1.62%	242	0.87%	2,083	1.23%
(14) Policy impact	242	0.45%	68	0.24%	417	0.25%
(15) Gender	1,257	2.34%	701	2.52%	551	0.33%
(16) Regional development	931	1.73%	710	2.55%	2,704	1.60%
(17) Communications	385	0.72%	287	1.03%	1,751	1.03%
(18) Immigration	425	0.79%	220	0.79%	1,218	0.72%
(19) Health system	2,149	4.00%	1,489	5.34%	4,682	2.76%
(20) International development	862	1.60%	687	2.47%	3,718	2.19%
(21) Benefits & disability	1,888	3.51%	317	1.14%	2,101	1.24%
(22) Sport & culture	846	1.57%	317	1.14%	2,628	1.55%
(23) History	299	0.56%	140	0.50%	1,720	1.02%
(24) Higher education & skills	974	1.81%	456	1.64%	3,501	2.07%
(25) Concurring point	33	0.06%	9	0.03%	139	0.08%
(26) Pensions	1,231	2.29%	529	1.90%	2,982	1.76%
(27) Points of order	787	1.46%	230	0.83%	4,069	2.40%
(28) Issues	1,618	3.01%	1,720	6.17%	6,745	3.98%
(29) Constituencies	125	0.23%	30	0.11%	228	0.13%
(30) Ethnic groups & racism	454	0.84%	203	0.73%	945	0.56%
(31) Amendments	526	0.98%	317	1.14%	2,293	1.35%
(32) Reports	536	1.00%	322	1.16%	1,488	0.88%
(33) People	2,818	5.24%	1,048	3.76%	9,136	5.39%
(34) Wales & Scotland	662	1.23%	224	0.80%	2,655	1.57%
(35) Alcohol & tobacco	846	1.57%	336	1.21%	2,357	1.39%
(36) Place names	163	0.30%	47	0.17%	447	0.26%
(37) Budget	1,616	3.00%	668	2.40%	5,567	3.29%
(38) Tax	2,149	4.00%	691	2.48%	4,562	2.69%
(39) Private companies	452	0.84%	362	1.30%	1,794	1.06%
(40) Environment & fishing	435	0.81%	186	0.67%	1,689	1.00%
(41) Crime	1,408	2.62%	926	3.32%	3,073	1.81%
(42) Bills	1,199	2.23%	931	3.34%	4,534	2.68%
(43) Children	1,176	2.19%	631	2.26%	1,298	0.77%
(44) Utilities & PFI	433	0.81%	175	0.63%	1,416	0.84%
(45) Middle East	1,284	2.39%	588	2.11%	4,543	2.68%
(46) Local authorities	1,050	1.95%	711	2.55%	3,686	2.18%
(47) Elections	759	1.41%	240	0.86%	4,308	2.54%

Table 10: Count and Distribution of Topics *(continued)*

Topic	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
(48) Debate	422	0.78%	128	0.46%	1,364	0.81%
(49) Transport	1,517	2.82%	546	1.96%	4,172	2.46%
(50) Questions	390	0.73%	182	0.65%	1,115	0.66%
(51) Families	786	1.46%	276	0.99%	1,169	0.69%
(52) Health research	743	1.38%	591	2.12%	1,467	0.87%
(53) Dispatch box	1	0.00%	NA	NA%	4	0.00%
(54) Parties	879	1.63%	438	1.57%	5,053	2.98%
(55) Statements	180	0.33%	79	0.28%	856	0.51%
(56) European Union	769	1.43%	554	1.99%	3,949	2.33%
(57) Locations	299	0.56%	126	0.45%	1,112	0.66%
(58) Jobs & manufacturing	1,426	2.65%	586	2.10%	4,162	2.46%
(59) Small business	229	0.43%	183	0.66%	791	0.47%
(60) Agreement & disagreement	523	0.97%	275	0.99%	4,962	2.93%
(61) Voluntary sector	1,307	2.43%	853	3.06%	2,480	1.46%
(62) Comments	108	0.20%	95	0.34%	865	0.51%
(63) Social care	865	1.61%	521	1.87%	1,187	0.70%
(64) Time	208	0.39%	103	0.37%	930	0.55%
(65) Media & animals	741	1.38%	190	0.68%	2,811	1.66%

3.6.1 Topic Graphs

The estimate effects in these graphs were extracted using the `tidystm` package by Mikael Poul Johannesson.[2] Figure 9 highlights nine topics with different expected proportions between male, AWS and non-AWS Labour MPs, with the error bars representing 95% confidence intervals. See Figure 10 for a graph of all 66 topics.

[2] Available online at: https://github.com/mikajoh/tidystm

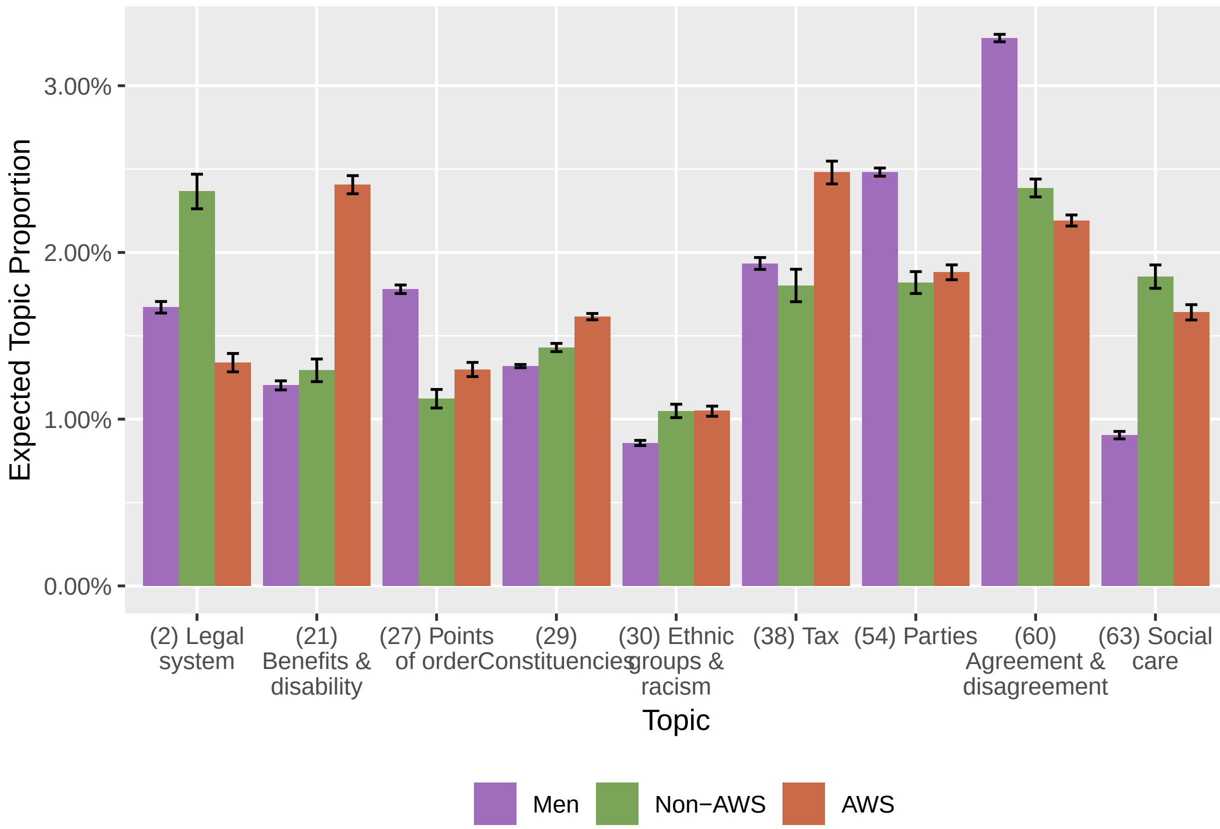

Figure 9: Selected Topic Proportions

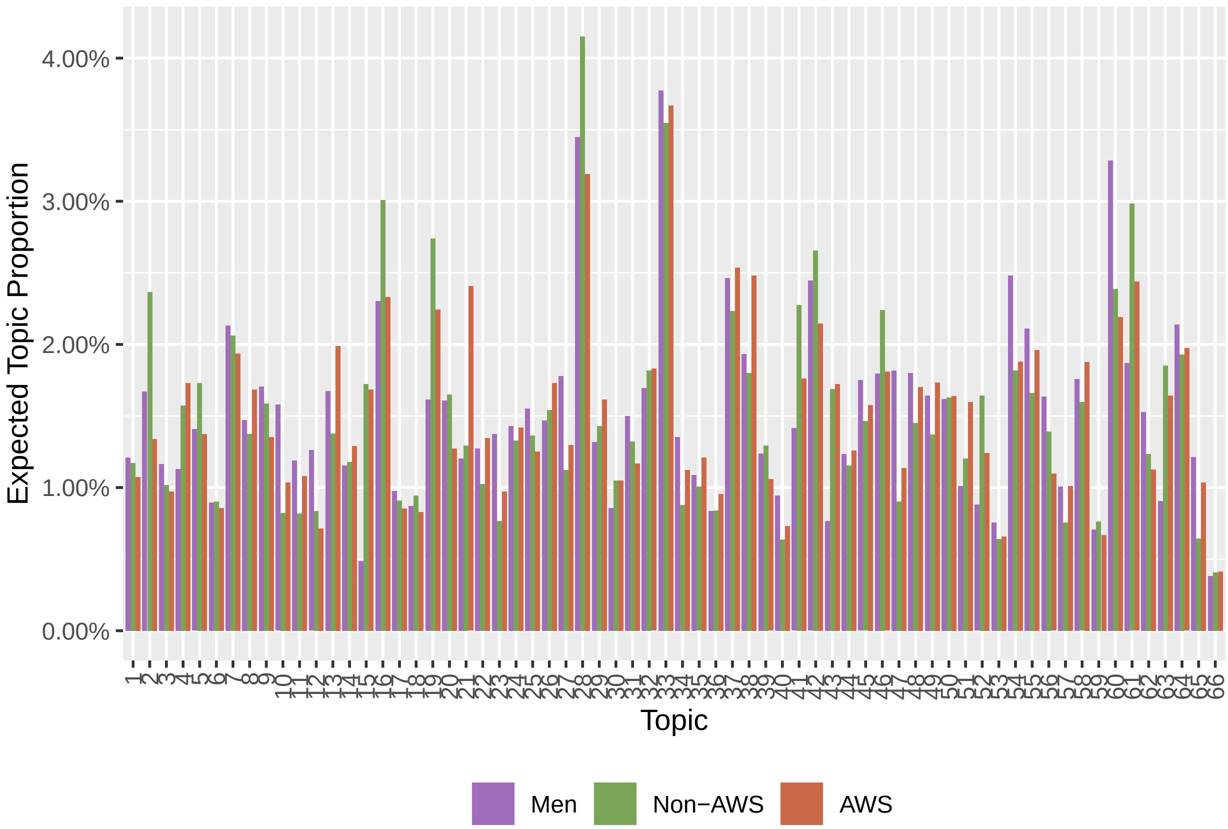

Figure 10: All Topic Proportions

3.6.2 Word Occurrences

The table below shows the twenty most common words in each topic, and the twenty words with the highest FREX score, a measure that uses a harmonic mean of word exclusivity and topic coherence (Airoldi & Bischof, 2016). We have named each topic based on the most common words and highest FREX score words in each topic.

Table 11: Words in Topic

Topic Number	Top Twenty Words	Top Twenty FREX
(1) Employment & unions	rights, workers, law, human, civil, trade, union, protection, employers, act, employment, unions, safety, employees, work, service, staff, employer, legislation, protect	tupe, blacklisting, acas, rights, gangmasters, civil, dispute, protections, unions, dismissal, servants, human, disputes, workers, employer, num, certification, employees, tuc, employers
(2) Legal system	cases, court, legal, case, justice, law, courts, evidence, lord, appeal, system, criminal, judicial, investigation, judge, aid, prosecution, circumstances, trial, lawyers	judicial, attorney-general, court, prosecutor, judges, carlile, defendant, extradition, cps, judiciary, admissible, pre-charge, jury, solicitors, lawyers, solicitor, courts, lawyer, detention, judge

Table 11: Words in Topic *(continued)*

Topic Number	Top Twenty Words	Top Twenty FREX
(3) Roads	road, planning, site, land, sites, car, vehicles, residents, roads, safety, use, driving, vehicle, park, development, traffic, drivers, area, cars, speed	bikes, cyclists, pedestrians, gypsy, off-road, cycling, encampments, parking, highways, masts, drivers, belt, roads, highway, road, gypsies, vehicles, site, vehicle, bike
(4) Housing	housing, homes, social, affordable, property, home, properties, london, accommodation, building, private, houses, tenants, rent, need, council, landlords, sector, buy, people	tenants, rent, landlords, rented, homelessness, rents, leaseholders, leasehold, tenancy, commonhold, hmos, housing, one-bedroom, homeless, properties, right-to-buy, affordable, sleepers, fulham, landlord
(5) Police, firefighters & prison	police, officers, crime, policing, service, fire, prison, home, force, chief, community, officer, staff, forces, neighbourhood, probation, prisons, safety, prisoners, resources	policing, firefighters, constables, pcsos, probation, csos, prisons, fire, constable, hmic, constabulary, officers, police, prison, prisoners, reoffending, neighbourhood, metropolitan, fires, ipcc
(6) Northern Ireland	make, sure, progress, northern, decisions, ireland, difference, towards, future, process, contribution, statement, responsibilities, easier, responsibility, must, departmental, belfast, friday, choices	sinn, fein, make, sure, belfast, northern, progress, ulster, difference, ireland, ruc, decisions, patten, dissident, departmental, taoiseach, antrim, imc, chastelain, dpps
(7) Committee	committee, report, review, commission, independent, government, select, process, evidence, inquiry, scrutiny, recommendations, role, board, set, work, reports, public, published, parliament	committee's, select, inquiry, scrutiny, recommendations, committee, committees, independent, recommendation, panel, pre-legislative, report, chairman, review, reviews, scrutinise, inquiries, conclusions, publication, findings
(8) Schools	schools, school, education, teachers, pupils, primary, children, standards, educational, special, secondary, parents, free, teacher, teaching, head, academies, academy, curriculum, good	schools, teachers, pupils, academies, pupil, grammar, classroom, leas, school's, academisation, school, teacher, bsf, academy, headteachers, ofsted, lea, literacy, curriculum, classrooms
(9) Energy & climate change	energy, climate, change, fuel, carbon, gas, power, emissions, waste, nuclear, prices, wind, green, environmental, electricity, oil, industry, efficiency, renewable, price	energy, carbon, electricity, renewable, renewables, solar, ofgem, greenhouse, co2, ccs, feed-in, biofuels, microgeneration, fossil, sellafield, decarbonisation, chp, shale, mw, bnfl
(10) Defence	defence, forces, armed, afghanistan, service, military, personnel, army, security, troops, support, ministry, royal, veterans, british, force, capability, iraq, equipment, also	armed, veterans, mod, regiment, legion, servicemen, reservists, helmand, battalion, ta, hms, gurkhas, regiments, marines, gurkha, fusiliers, ex-service, eurofighter, isaf, afghan

Table 11: Words in Topic *(continued)*

Topic Number	Top Twenty Words	Top Twenty FREX
(11) Parliament	house, leader, motion, commons, therefore, parliament, petition, parliamentary, government, urge, present, signed, table, notes, library, behalf, remain, floor, westminster, request	petitioners, declares, petition, house, motion, urges, commons, serjeant, recess, notes, leader, motions, lobbyist, thursday, early-day, e-petitions, house's, tuesday, session, lobbying
(12) International politics	united, states, agreement, kingdom, foreign, treaty, council, security, us, nuclear, president, co-operation, convention, nations, national, policy, article, russia, international, position	lisbon, ratification, treaty, non-proliferation, treaties, qmv, ratified, veto, gibraltar, ukraine, russia, agreement, protocol, states, united, ratify, russian, kingdom's, hague, disarmament
(13) Ministers	secretary, state, statement, ministers, today, confirm, department, government's, explain, yesterday, home, plans, announcement, government, welcome, chief, state's, urgent, ministerial, announced	secretary, state, state's, confirm, ministers, yesterday, announcement, ministerial, explain, statement, expects, urgent, intends, assurances, yesterday's, secretaries, secretary's, update, leaked, cabinet
(14) Policy impact	made, clear, number, decision, impact, changes, recent, assessment, effect, level, discussions, likely, proposed, colleagues, potential, representations, implications, analysis, effects, result	made, clear, decision, assessment, recent, changes, impact, representations, implications, effect, discussions, analysis, assess, implementation, estimate, level, number, negative, outcome, colleagues
(15) Gender	women, men, violence, equality, domestic, age, discrimination, women's, equal, pay, woman, girls, gender, sexual, sex, female, gap, government, maternity, male	women's, gender, transgender, breastfeeding, refuges, women, abortions, fgm, shortlists, female, male, equality, girls, all-women, gay, equalities, lesbian, men, pregnancy, fawcett
(16) Regional development	new, development, future, programme, national, strategy, government, regional, key, plan, department, welcome, paper, set, ensure, commitment, support, improve, need, deliver	strategy, regional, programme, projects, paper, plan, project, deliver, white, key, development, delivering, develop, priorities, partnership, improve, framework, new, priority, improving
(17) Communications	office, post, bank, banks, rural, offices, services, service, royal, banking, network, mail, closure, access, areas, broadband, card, account, staff, closures	offices, mail, sub-postmasters, sub-post, superfast, post, postwatch, postcomm, consignia, broadband, rbs, office, banking, mail's, bank, lloyds, ons, uso, branches, banks
(18) Immigration	british, uk, rules, home, immigration, citizens, asylum, identity, status, country, overseas, application, indicated, applications, apply, border, abroad, cards, migration, entry	passports, nationality, dissent, immigration, passport, indicated, points-based, identity, asylum, nationals, visa, dependencies, migration, migrants, biometric, overseas, citizen, entry, abroad, monarch

Table 11: Words in Topic *(continued)*

Topic Number	Top Twenty Words	Top Twenty FREX
(19) Health system	health, nhs, hospital, service, patients, services, mental, trust, staff, hospitals, care, trusts, patient, primary, waiting, doctors, nurses, e, gp, emergency	in-patient, helier, nurses, chcs, nhs, ccgs, ccg, sha, hospital's, hospital, fundholding, pct, hospitals, mental, gp, healthwatch, orthopaedic, walk-in, trusts, reconfiguration
(20) International development	international, countries, world, aid, development, government, developing, africa, global, uk, support, trade, poverty, country, india, assistance, un, need, also, nations	zimbabwe, dfid, burma, congo, cdc, kenya, burmese, doha, uganda, mugabe, sub-saharan, g8, zimbabwean, dfid's, gleneagles, african, sri, lanka, cancun, nigeria
(21) Benefits & disability	people, benefit, work, benefits, disabled, support, allowance, welfare, employment, disability, system, government, help, universal, credit, reform, get, vulnerable, plus, living	incapacity, dla, esa, jobcentre, disabled, jobseeker's, jsa, disability, allowance, dwp, claimants, atos, benefit, plus, claiming, pip, motability, benefits, deaf, bedroom
(22) Sport & culture	city, centre, town, sport, football, community, liverpool, sports, club, constituency, clubs, culture, london, great, facilities, one, bid, games, towns, regeneration	football, olympic, museum, museums, stadium, athletes, cricket, paralympic, games, gospels, sports, club, sporting, fans, cup, rugby, arts, olympics, sport, galleries
(23) History	history, former, world, tribute, great, day, never, proud, first, remember, new, john, campaign, century, parliament, pay, also, war, today, sir	maiden, miners, memorial, predecessors, hillsborough, tony, martin, james, john, william, andrew, margaret, anniversary, peter, alan, memories, fought, harold, churchill, edward
(24) Higher education & skills	education, skills, students, university, training, higher, young, universities, college, learning, science, apprenticeships, colleges, fees, student, funding, research, system, qualifications, courses	universities, student, apprenticeship, fe, graduates, ema, graduate, students, colleges, diploma, apprenticeships, vocational, leitch, esol, qualifications, courses, undergraduate, university, tuition, sixth-form
(25) Concurring point	point, agree, country, making, makes, absolutely, whole, much, good, part, friend's, entirely, completely, kind, sense, giving, rather, share, precisely, parts	agree, absolutely, makes, friend's, point, precisely, making, entirely, completely, kind, whole, sense, direction, mentions, refers, gentleman's, describes, powerful, danger, exactly
(26) Pensions	scheme, pension, credit, pensions, insurance, schemes, pensioners, payments, compensation, fund, payment, money, financial, paid, savings, debt, retirement, government, pay, income	pension, annuity, policyholders, annuities, auto-enrolment, insurance, retirement, loan, payments, payday, scheme, compensation, equitable, premiums, payment, pensions, means-testing, lenders, savers, pensioners
(27) Points of order	question, order, mr, put, speaker, deputy, point, grateful, read, agreed, record, time, minutes, may, call, standing, correct, apologise, madam, interventions	speaker, mr, madam, question, forthwith, deputy, apologise, order, o'clock, read, minutes, adjourned, accordingly, interventions, hansard, tomorrow, grateful, misled, correct, courtesy

Table 11: Words in Topic *(continued)*

Topic Number	Top Twenty Words	Top Twenty FREX
(28) Issues	important, issue, can, issues, take, ensure, hope, need, matter, consider, possible, place, also, concerns, deal, particular, course, taken, concern, raised	issues, issue, important, concerns, consider, possible, discuss, concern, particular, matter, considering, carefully, assure, understand, extremely, raised, addressed, obviously, address, expressed
(29) Constituencies	many, constituency, constituents, problems, welcome, particularly, people, often, hard, face, others, feel, country, especially, worked, pay, concerned, represent, thousands, large	many, constituents, problems, hard, mine, worked, difficulties, faced, represent, feel, constituencies, thousands, hundreds, face, greatly, often, constituency, especially, worried, experienced
(30) Ethnic groups & racism	action, taking, community, steps, taken, communities, take, actions, society, prevent, faith, groups, minority, church, black, ethnic, religious, freedom, race, diversity	religion, faiths, sikh, steps, racial, faith, sikhs, religious, priests, synod, beliefs, church, racism, taking, action, ethnic, anglican, hate, clergy, hatred
(31) Amendments	clause, amendment, amendments, new, lords, section, 1, tabled, 2, clauses, line, 3, leave, act, shall, move, beg, 4, page, schedule	insert, nos, subsection1, amendmenta, amendment, subsection5, 1a, schedule, amendmentsa, amendments, subsection2, subsection6, clause, tabled, paragrapha, subsection, subsection3, andc, paragraphb, clauses
(32) Reports	year, since, report, number, figures, official, march, april, published, 1997, figure, statistics, 15, 30, show, january, 2010, july, june, december	vol, october, march, official, february, july, january, november, june, april, 2011, statistics, since, 2009, 2007, december, 2005, figures, 2013, figure
(33) People	people, want, get, one, go, can, think, see, need, know, say, things, much, like, good, going, problem, done, something, put	things, get, something, go, lot, want, talking, thing, trying, talk, think, really, quite, bit, else, happen, away, getting, enough, idea
(34) Wales & Scotland	wales, scotland, scottish, england, welsh, assembly, parliament, devolution, uk, devolved, government, powers, kingdom, national, english, united, glasgow, executive, snp, edinburgh	scotland, scottish, welsh, snp, scotland's, cymru, barnett, plaid, perth, wishart, holyrood, perthshirepete, wales, snp's, assembly, devolved, dundee, scots, devolution, calman
(35) Alcohol & tobacco	food, industry, alcohol, licensing, products, smoking, shops, shop, tobacco, advertising, health, standards, pub, pubs, high, buy, drinking, supermarkets, problem, retailers	tobacco, pubs, gambling, betting, labelling, drinks, cigarettes, casinos, smokers, cigarette, groceries, lap-dancing, vending, drinkers, supermarkets, fluoride, smoking, pubcos, pub, retailers
(36) Place names	thank, south, constituency, north, excellent, join, congratulate, manchester, area, yorkshire, north-west, reply, visit, greater, visited, also, bristol, nottingham, giving, region	thank, wrexham, reddish, tameside, congratulating, newport, yorkshire, stockport, blaenau, derbyshire, south, north-west, stoke-on-trent, denbighshire, denton, nottingham, bristol, welcoming, newingtonms, congratulations

Table 11: Words in Topic *(continued)*

Topic Number	Top Twenty Words	Top Twenty FREX
(37) Budget	million, budget, year, billion, cuts, chancellor, spending, cut, increase, money, government, 1, funding, extra, next, investment, deficit, financial, crisis, growth	deficit, obr, billion, spending, budget, real-terms, forecast, million, borrowing, cuts, gdp, chancellor, cut, 2.5, chancellor's, forecasts, 2010-11, 1.2, 1.5, finances
(38) Tax	tax, pay, rate, income, wage, families, minimum, living, low, poverty, working, vat, increase, government, paid, national, paying, credits, average, poorest	tax, millionaires, 50p, vat, taxes, credits, wage, taxation, avoidance, incomes, rate, zero-hours, wages, 45p, earning, revaluation, income, richest, earners, regressive
(39) Private companies	companies, company, market, financial, industry, competition, consumers, interest, consumer, assets, services, profits, markets, ownership, regulator, share, corporate, interests, customers, societies	mutuals, shareholders, provident, company, companies, competition, profits, corporate, shares, company's, societies, co-operative, fsa, co-operatives, profit, directors, rock, regulator, assets, asset
(40) Environment & fishing	environment, sea, fishing, marine, fisheries, industry, natural, fish, port, environmental, water, ports, rural, coastal, protection, conservation, fishermen, areas, management, area	fishing, fisheries, fishermen, cod, seas, whitby, coastguard, broads, cfp, angling, seafarers, anglers, inshore, discards, mmo, under-10, sssis, dredging, cockle, aonbs
(41) Crime	crime, behaviour, victims, offence, criminal, serious, abuse, offences, antisocial, home, use, measures, drugs, drug, enforcement, offenders, problem, tackle, law, justice	sentences, asbos, cannabis, antisocial, offences, offence, trafficking, gangs, behaviour, penalty, sentencing, sentence, theft, criminals, custodial, offending, knife, heroin, offenders, victim
(42) Bills	bill, legislation, act, new, powers, provisions, regulations, power, place, provision, duty, apply, statutory, necessary, allow, provide, set, already, introduce, require	provisions, bill, bill's, definition, legislation, regulations, statutory, passage, seeks, requirement, drafted, draft, statute, intention, safeguards, purpose, consult, legislative, amend, covered
(43) Children	children, child, parents, families, children's, support, poverty, family, young, needs, parent, start, adoption, adults, vulnerable, early, contact, must, need, autism	autism, csa, looked-after, adoptive, child, adopters, children's, autistic, cafcass, nspcc, child's, children, parent, dyslexia, adoption, kinship, childcare, intercountry, parents, lone
(44) Utilities & PFI	public, private, sector, money, costs, cost, risk, value, management, service, water, government, contracts, contract, system, audit, flood, systems, agency, taxpayer	id, flood, nao, ofwat, public, contracts, private, auditor, purse, contractors, audit, pac, pfi, flooding, taxpayer, floods, contract, comptroller, tendering, defences
(45) Middle East	security, government, peace, war, foreign, people, iraq, terrorism, international, conflict, threat, support, must, un, military, syria, israel, resolution, terrorist, refugees	syria, israel, palestinian, israeli, gaza, palestinians, syrian, saddam, arab, hamas, saudi, daesh, palestine, isil, israelis, hussein, lebanon, atrocities, assad, two-state

Table 11: Words in Topic *(continued)*

Topic Number	Top Twenty Words	Top Twenty FREX
(46) Local authorities	local, authorities, council, authority, areas, government, funding, area, councils, communities, county, grant, planning, community, central, formula, borough, locally, level, resources	local, authorities, councillors, councils, authority, unitary, county, formula, grant, lga, locally, localism, swindon, allocations, allocation, deprived, council, parish, authority's, deprivation
(47) Elections	vote, political, parliament, electoral, election, elections, elected, parties, people, voting, referendum, democracy, register, system, registration, democratic, commission, party, votes, majority	electoral, voters, turnout, voter, all-postal, votes, vote, voting, polling, first-past-the-post, av, referendums, elections, unelected, registration, ballot, candidates, electors, electorate, elected
(48) Debate	members, debate, speech, heard, today, hope, opportunity, speak, hear, chamber, great, wish, support, time, pleased, debates, sides, like, follow, subject	debate, speech, members, debates, speeches, speak, heard, listened, sides, debating, hear, speaking, tonight, pleasure, chamber, thoughtful, listening, afternoon, queen's, cross-party
(49) Transport	london, transport, rail, bus, services, line, network, travel, airport, train, air, service, passengers, trains, railway, station, east, capacity, passenger, heathrow	rail, bus, passengers, trains, passenger, heathrow, railways, fares, freight, crossrail, hs2, high-speed, runway, electrification, airlines, gatwick, caa, baa, sra, thameslink
(50) Questions	whether, information, may, answer, asked, ask, questions, response, available, advice, received, data, know, press, written, letter, department, meeting, details, officials	answer, information, questions, answers, data, written, details, letter, write, ask, officials, answered, asked, whether, informed, press, website, correspondence, response, requests
(51) Families	family, life, families, lives, constituent, death, home, people, told, case, one, man, died, lost, mrs, person, mother, day, marriage, suffered	husband, mum, daughter, constituent, married, mrs, son, mother, marriage, died, father, wife, same-sex, death, loved, dad, suicide, funeral, bereaved, boy
(52) Health research	research, treatment, cancer, medical, disease, health, drugs, condition, can, use, drug, patients, screening, risk, also, conditions, evidence, group, diseases, diagnosis	screening, asbestos, tissue, embryos, cancers, hepatitis, genetic, prostate, epilepsy, cloning, pleural, fertilisation, embryo, embryonic, ivf, anaemia, embryology, piercing, hfea, bowel
(53) Dispatch box	back, come, look, forward, bring, moment, coming, comes, side, later, brought, along, bringing, round, looking, box, see, putting, sit, dispatch	come, back, look, moment, forward, dispatch, coming, comes, side, box, oh, surprise, bring, round, hoping, bringing, sooner, straight, along, sit
(54) Parties	government, labour, conservative, party, opposition, policy, previous, liberal, conservatives, government's, support, election, tory, front, democrats, coalition, benches, policies, general, fact	conservative, conservatives, liberal, democrats, lib, tory, democrat, benches, tories, opposition, manifesto, party's, labour, benchers, dem, opposition's, front-bench, party, spokesman, bench
(55) Statements	us, said, just, let, say, now, tell, says, yet, saying, told, know, going, nothing, wrong, even, wants, words, minister's, today	tell, says, let, wants, us, actually, saying, minister's, telling, truth, wrong, wonder, thinks, nothing, promise, afraid, mistake, blame, admit, honest

Table 11: Words in Topic *(continued)*

Topic Number	Top Twenty Words	Top Twenty FREX
(56) European Union	european, eu, europe, union, uk, countries, britain, trade, single, british, negotiations, market, economic, france, germany, country, leave, membership, referendum, world	euro, ttip, brexit, accession, eu, currencies, cypriots, european, eurozone, europe, enlargement, pro-european, spain, currency, esm, france, greece, italy, brussels, isds
(57) Locations	member, west, east, north, birmingham, friends, st, spoke, hull, sheffield, talked, leeds, leicester, midlands, upon, newcastle, westmr, eastmr, northmr, southmr	kingston, eastmr, bromley, chislehurstmr, holborn, dorsetmr, northmr, enfield, hull, southmr, chislehurst, stuart, ealing, rees-mogg, leicester, chingford, westmr, greenmr, southend, letwin
(58) Jobs & manufacturing	jobs, economy, economic, growth, industry, unemployment, investment, government, uk, manufacturing, future, sector, employment, country, job, long-term, steel, north-east, industries, recession	steel, manufacturing, jobs, tata, economy, teesside, unemployment, recession, automotive, downturn, steelworkers, productivity, inward, growth, industries, recessions, nissan, economic, steelworks, double-dip
(59) Small business	business, small, businesses, regulation, rates, enterprise, government, finance, support, firms, help, innovation, measures, regulatory, smaller, large, lending, enterprises, burden, larger	smes, medium-sized, businesses, business, enterprises, small, regulation, enterprise, commerce, entrepreneurs, tape, firms, lending, burdens, brs, start-up, start-ups, entrepreneurial, lend, smaller
(60) Agreement & disagreement	believe, however, one, might, accept, must, different, case, system, view, change, think, whether, position, argument, rather, simply, reason, basis, although	accept, argument, principle, view, arguments, reason, might, argue, perfectly, suggest, balance, believe, suggesting, different, reasons, necessarily, sensible, disagree, argued, whatever
(61) Voluntary sector	work, people, young, support, help, can, working, organisations, role, voluntary, ensure, together, good, also, need, important, encourage, opportunities, experience, society	voluntary, organisations, charities, volunteering, young, charity, youth, work, opportunities, helping, encourage, volunteers, encouraging, play, charitable, working, help, ways, valuable, together
(62) Comments	member, said, shall, mentioned, earlier, points, lady, comments, referred, learned, intervention, remarks, interesting, raised, pointed, perhaps, gave, say, refer, described	comments, remarks, lady, interesting, points, happily, southwark, referred, bermondsey, referring, somerton, intervention, shall, intervened, mentioned, pointed, learned, earlier, gentlemen, rushcliffemr
(63) Social care	care, services, social, carers, people, need, service, needs, support, provision, older, provide, quality, home, centres, access, elderly, provided, providers, homes	carers, hospices, dentists, dental, care, dementia, hospice, dentistry, respite, carer, advocacy, elderly, older, caring, palliative, milton, dentist, social, keynes, cared
(64) Time	years, time, last, two, one, first, now, three, past, week, months, next, ago, every, 10, five, four, weeks, days, six	years, three, two, last, months, ago, past, time, four, week, weeks, six, five, first, next, days, 10, seven, half, now

Table 11: Words in Topic *(continued)*

Topic Number	Top Twenty Words	Top Twenty FREX
(65) Media & animals	bbc, farmers, digital, television, internet, animals, animal, media, radio, dogs, licence, dog, news, ban, farming, welfare, hunting, fee, online, farm	bbc, dogs, hunting, cull, bbc's, badgers, badger, bovine, switchover, broadcasters, gm, fur, mink, poultry, circuses, analogue, hare, hounds, puppies, swine
(66) Other	given, can, aware, may, recently, across, welcome, fact, government, well, take, close, result, seeking, indeed, support, confident, responsible, know, including	given, aware, can, recently, may, across, close, welcome, fact, confident, seeking, result, well, take, responsible, indeed, keep, regret, far, reconsider

3.6.3 Manual Validation

We have validated both the topics produced by the model and our labels of those topics to ensure the topics themselves are both interesting and relevant. Validation is particularly important in unsupervised models including STM (Grimmer & Stewart, 2013). Quinn, Monroe, Colaresi, Crespin, & Radev (2010) suggest that topics are valid if they correspond to external events. Figure 11 shows the number of speeches by Labour MPs on the "Middle East" topic, with a spike in 2003 (at the start of the Iraq War), another spike in 2008 and 2009, as the bulk of British troops left Iraq, a small spike in 2011 coinciding with UK participation in NATO's military intervention in Libya, and another spike resulting from debate in 2014–2016 over UK participation in military interventions in the Syrian Civil War.

Figure 12 shows debate over the devolved authorities of Wales and Scotland peaking in 2014, to coincide with Scotland's independence referendum. The post-2015 decline also likely stems from the SNP winning all but three seats in Scotland during the 2015 General Election. Figure 13 shows the increase in debate over the European Union coinciding with the referendum on the UK's member of the European Union.

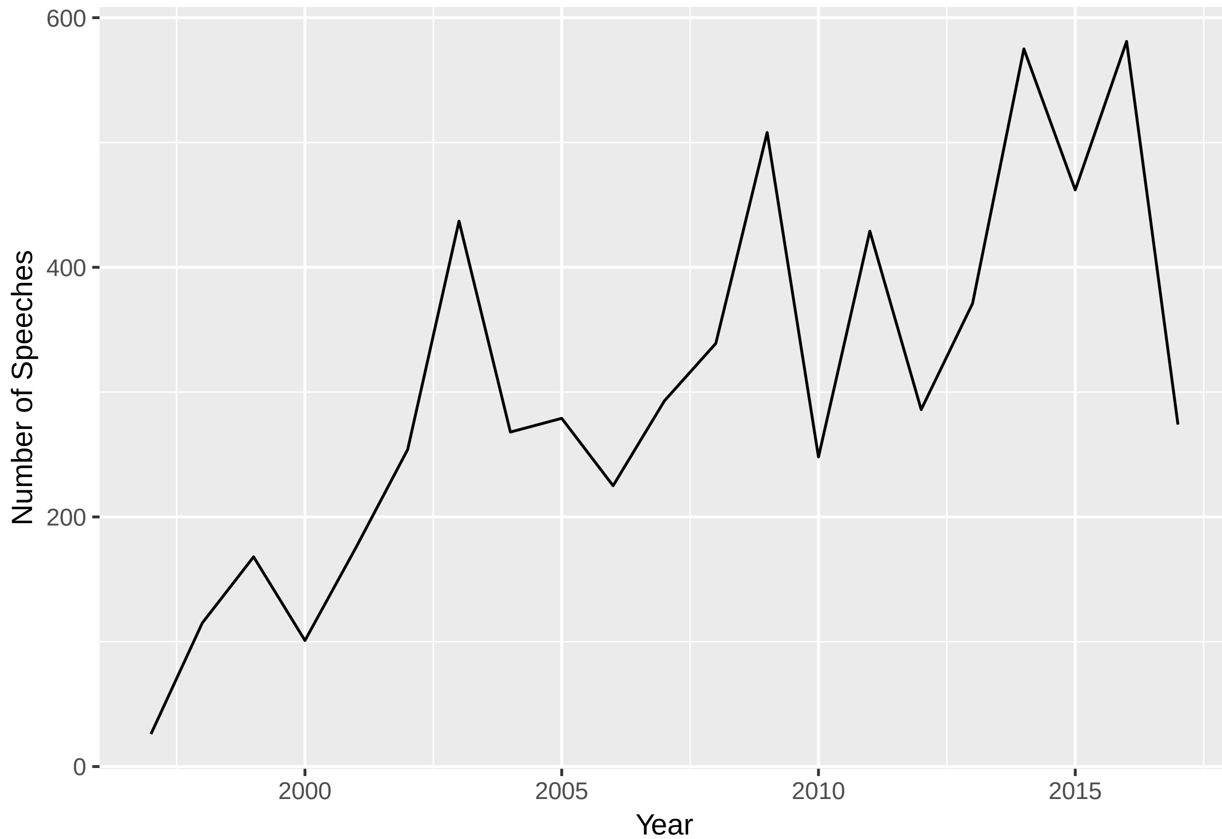

Figure 11: Number of Speeches in “Middle East” Topic per Year

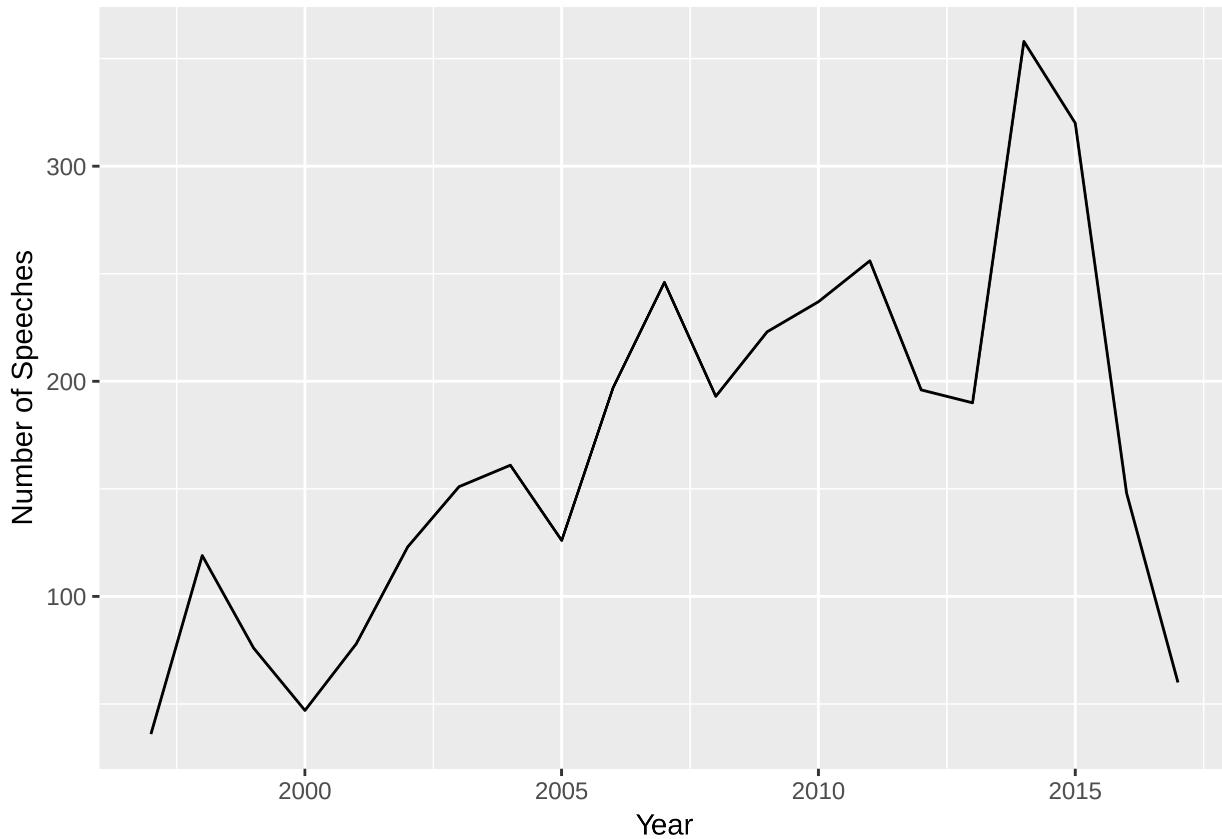

Figure 12: Number of Speeches in “Wales & Scotland” Topic per Year

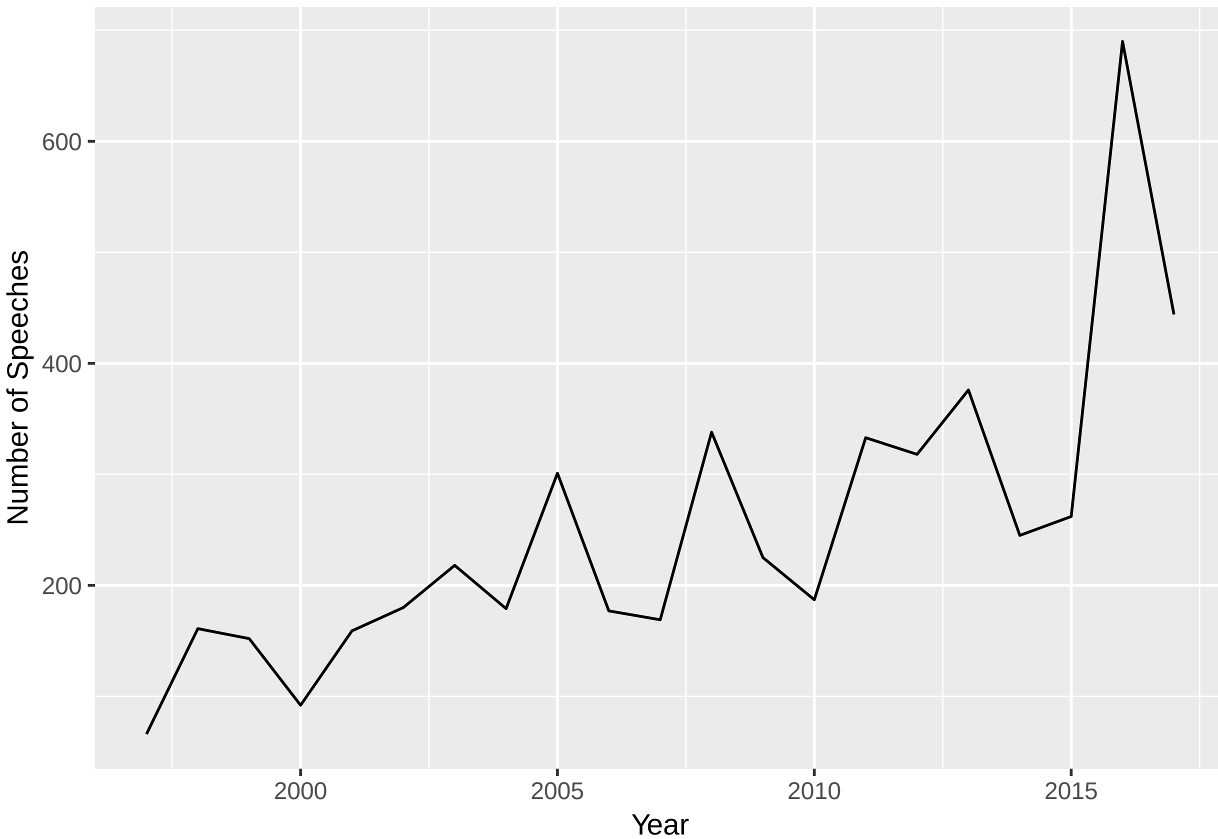

Figure 13: Number of Speeches in “European Union” Topic per Year

3.7 Differences between Male, AWS and non-AWS Labour MPs

From Table 9 we can see the relationship between the frequency of topics among AWS, non-AWS and male Labour MPs.

There are 11 topics where the frequency AWS MPs is significantly different from male MPs, but where its frequency amongst non-AWS MPs is not significantly different. They are topics 1, 6, 7, 8, 14, 17, 20, 26, 35, 36, 39. 5 topics are proportionally greater among AWS MPs (Topic 8, Schools, Topic 14, Policy impact, Topic 26, Pensions, Topic 35, Alcohol & tobacco, Topic 36, Place names) and 6 topics are less common (Topic 1, Employment & unions, Topic 6, Northern Ireland, Topic 7, Committee, Topic 17, Communications, Topic 20, International development, Topic 39, Private companies).

There are 7 topics where its proportion amongst non-AWS MPs is significantly different from male MPs, but where its proportion amongst AWS MPs is not significantly different. They are topics 5, 16, 24, 37, 44, 46, 57. 5 topics are proportionally greater among AWS MPs (Topic 16, Regional development, Topic 37, Budget, Topic 44, Utilities & PFI, Topic 46, Local authorities, Topic 57, Locations) and 2 topics are less common (Topic 5, Police, firefighters & prison, Topic 24, Higher education & skills).

There is 1 topic (Topic 50, Questions) where there is no significant difference in frequency among both AWS and non-AWS MPS, relative to male Labour MPs.

There are 10 topics where AWS and non-AWS MPs differ significantly in proportion from male Labour MPs, but are not both higher/lower than male MPs. AWS MPs are significantly more likely to mention 5 topics (Topic 13, Ministers, Topic 22, Sport & culture, Topic 38, Tax, Topic 49, Transport, Topic 58, Jobs & manufacturing) than male MPs, while non-AWS mps are significantly less likely to mention those topics. The opposite is true for the other 5 topics (Topic 2, Legal system, Topic 18, Immigration, Topic 28, Issues, Topic 42, Bills, Topic 59, Small business), which AWS MPs are significantly less likely and non-AWS MPs are significantly more likely to mention than male Labour MPs.

Using the frequency of a topic among male MPs as a baseline, there are 35 topics where the frequency among AWS MPs is proportionally closer, in absolute terms, than the frequency of the topic among female MPs. The inverse is true for the remaining 31 topics.

Relative to each other, there are 34 topics where the frequency between AWS and non-AWS MPs are closer to each other than either is to the topic frequency in male MPs. In 18 topics, the frequency between AWS and male MPs are the most similar, and in the remaining 14 topics the difference in frequency are smallest between non-AWS and male MPs. See 12 for details.

Table 12: Absolute Differences

Topic	Women Relative to Male MPs	Most Similar
(1) Employment & unions	Non-AWS more like male	Non-AWS more like male
(2) Legal system	AWS more like male	AWS more like male
(3) Roads	Non-AWS more like male	Women more similar to each other
(4) Housing	Non-AWS more like male	Women more similar to each other
(5) Police, firefighters & prison	AWS more like male	AWS more like male
(6) Northern Ireland	Non-AWS more like male	Non-AWS more like male
(7) Committee	Non-AWS more like male	Women more similar to each other
(8) Schools	Non-AWS more like male	Non-AWS more like male
(9) Energy & climate change	Non-AWS more like male	Women more similar to each other
(10) Defence	AWS more like male	Women more similar to each other
(11) Parliament	AWS more like male	AWS more like male
(12) International politics	Non-AWS more like male	Women more similar to each other
(13) Ministers	Non-AWS more like male	Non-AWS more like male
(14) Policy impact	Non-AWS more like male	Non-AWS more like male
(15) Gender	AWS more like male	Women more similar to each other
(16) Regional development	AWS more like male	AWS more like male
(17) Communications	Non-AWS more like male	Women more similar to each other
(18) Immigration	AWS more like male	AWS more like male
(19) Health system	AWS more like male	Women more similar to each other
(20) International development	Non-AWS more like male	Non-AWS more like male
(21) Benefits & disability	Non-AWS more like male	Non-AWS more like male
(22) Sport & culture	AWS more like male	AWS more like male
(23) History	AWS more like male	Women more similar to each other
(24) Higher education & skills	AWS more like male	AWS more like male
(25) Concurring point	Non-AWS more like male	Women more similar to each other
(26) Pensions	Non-AWS more like male	Non-AWS more like male
(27) Points of order	AWS more like male	Women more similar to each other
(28) Issues	AWS more like male	AWS more like male
(29) Constituencies	Non-AWS more like male	Women more similar to each other
(30) Ethnic groups & racism	Non-AWS more like male	Women more similar to each other
(31) Amendments	Non-AWS more like male	Women more similar to each other
(32) Reports	Non-AWS more like male	Women more similar to each other
(33) People	AWS more like male	Women more similar to each other
(34) Wales & Scotland	AWS more like male	Women more similar to each other
(35) Alcohol & tobacco	Non-AWS more like male	Non-AWS more like male
(36) Place names	Non-AWS more like male	Non-AWS more like male

Table 12: Absolute Differences *(continued)*

Topic	Women Relative to Male MPs	Most Similar
(37) Budget	AWS more like male	AWS more like male
(38) Tax	Non-AWS more like male	Non-AWS more like male
(39) Private companies	Non-AWS more like male	Non-AWS more like male
(40) Environment & fishing	AWS more like male	Women more similar to each other
(41) Crime	AWS more like male	Women more similar to each other
(42) Bills	Non-AWS more like male	Non-AWS more like male
(43) Children	Non-AWS more like male	Women more similar to each other
(44) Utilities & PFI	AWS more like male	AWS more like male
(45) Middle East	AWS more like male	Women more similar to each other
(46) Local authorities	AWS more like male	AWS more like male
(47) Elections	AWS more like male	Women more similar to each other
(48) Debate	AWS more like male	AWS more like male
(49) Transport	AWS more like male	AWS more like male
(50) Questions	Non-AWS more like male	Women more similar to each other
(51) Families	Non-AWS more like male	Non-AWS more like male
(52) Health research	AWS more like male	Women more similar to each other
(53) Dispatch box	AWS more like male	Women more similar to each other
(54) Parties	AWS more like male	Women more similar to each other
(55) Statements	AWS more like male	AWS more like male
(56) European Union	Non-AWS more like male	Women more similar to each other
(57) Locations	AWS more like male	AWS more like male
(58) Jobs & manufacturing	AWS more like male	AWS more like male
(59) Small business	AWS more like male	AWS more like male
(60) Agreement & disagreement	Non-AWS more like male	Women more similar to each other
(61) Voluntary sector	AWS more like male	Women more similar to each other
(62) Comments	Non-AWS more like male	Women more similar to each other
(63) Social care	AWS more like male	Women more similar to each other
(64) Time	AWS more like male	Women more similar to each other
(65) Media & animals	AWS more like male	AWS more like male
(66) Other	Non-AWS more like male	Women more similar to each other

On the hypothesis that non-AWS MPs are more similar to male MPs in their topic selection, the following are topics with the largest absolute differences between AWS and other MPs.

Figure 14 shows the frequency for the topics where AWS and non-AWS MPs differ the most. Figure 15 shows the frequency for the topics where AWS and non-AWS MPs are most similar to each other, regardless of their similarity to male Labour MPs. Figure 16 is the topics with the most variation, between AWS, non-AWS and male Labour MPs. Figures 14, 15 and 16 all use the coefficient of variation to measure variance between each group of MPs. Figures 14 and 15 only use female Labour MPS, Figure 16 uses all three groups.

- Measuring and comparing Coefficients of Variation
- use the CV equality function to compare variations?

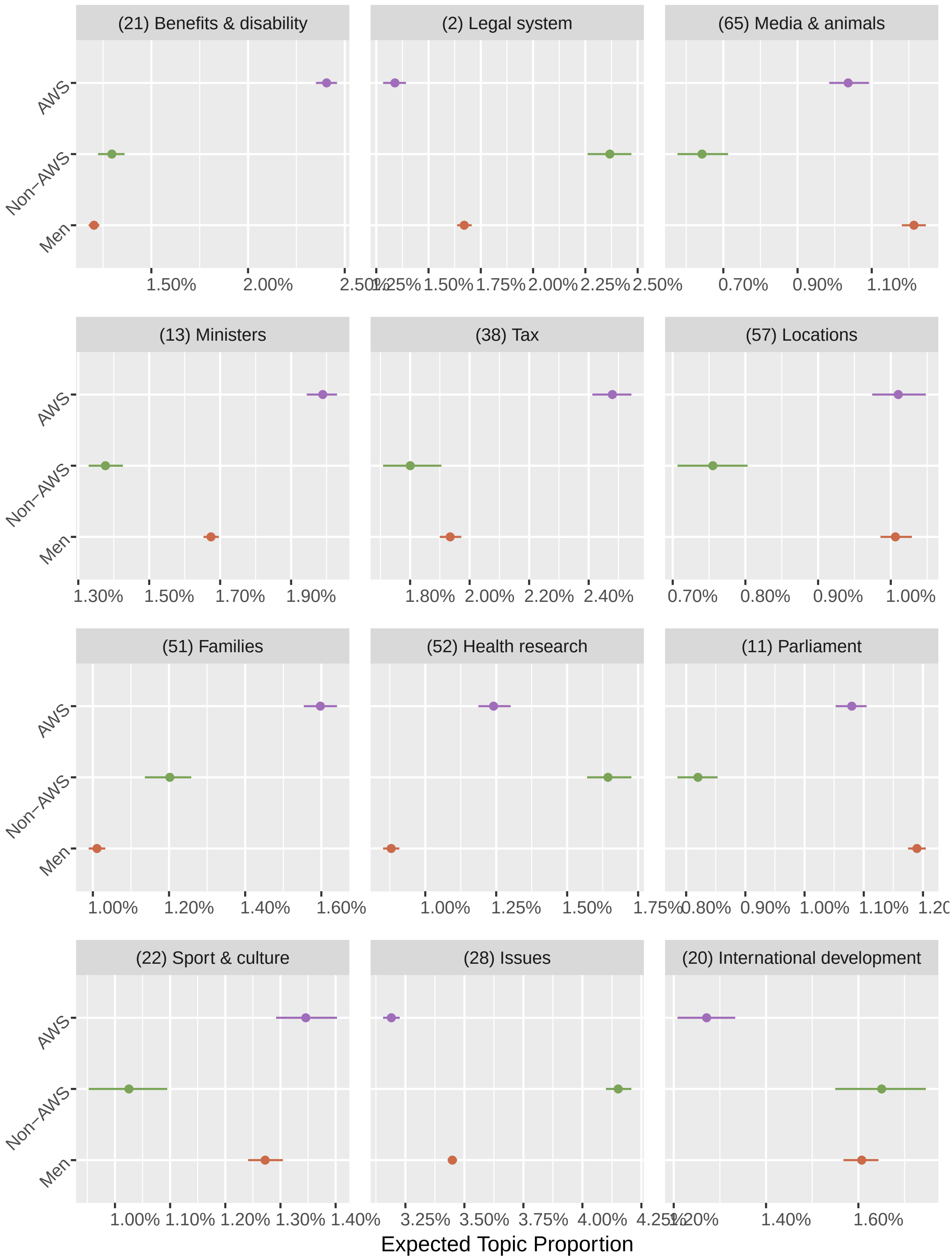

Figure 14: Where AWS MPs are most distinct from non-AWS female MPs

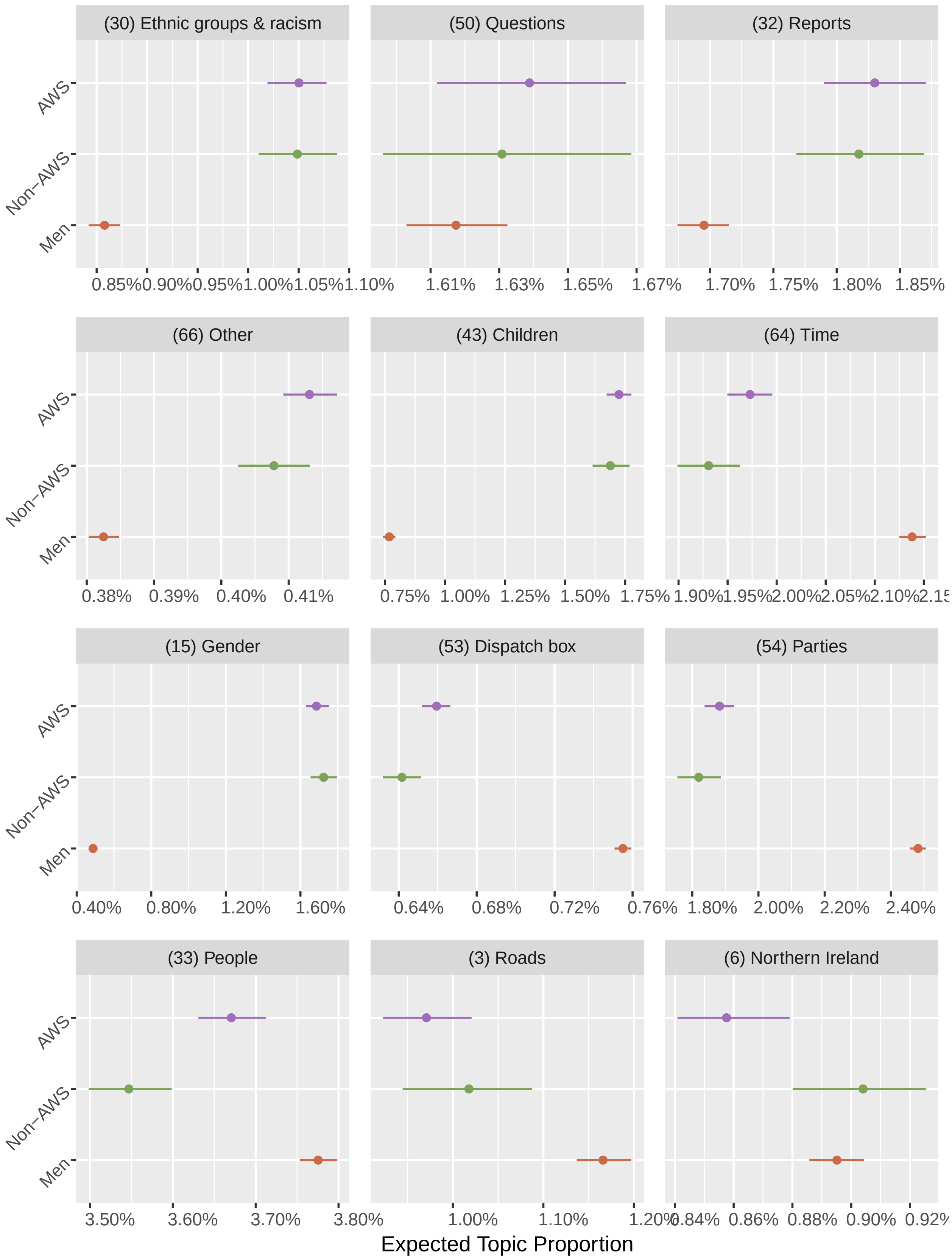

Figure 15: Where AWS MPs are most similar to non-AWS female MPs

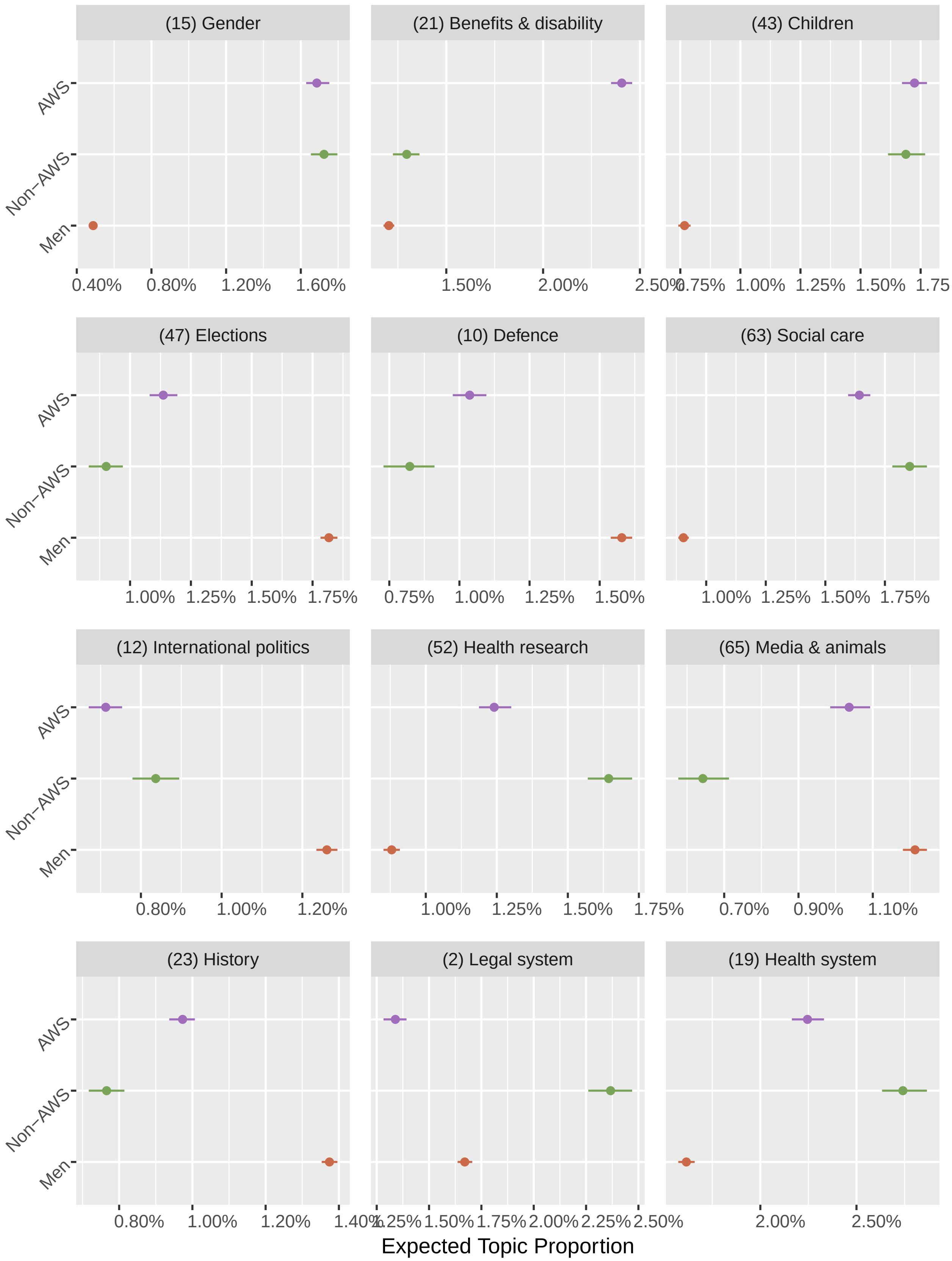

Figure 16: Topics with the greatest frequency coefficient of variation

[Stuff on categories with extensive differences]

4 Discussion

There do not appear to be substantial or meaningful differences in the speaking styles of female Labour MPs selected through all women shortlists when compared to their female colleagues selected through open shortlists using LIWC. This is possibly due to the speaking style dominant in British parliamentary debate, which is more formal than the speech used in most day-to-day conversation. LIWC was developed by American researchers, and the LIWC dictionary may not be able to capture stylistic differences between American and British English, and may not include words commonly used in formal British English speech, limiting its usefulness in the context of British political debate.

There is more distinction between AWS and non-AWS MPs in terms and topics. Naive Bayes classification was able to accurately determine the AWS status of female Labour MPs with slightly greater accuracy than it could distinguish between male and female Labour MPs (71.22% and 70.67%, respectively).

AWS MPs are far more likely to make reference to their constituency and constituents. In the debate between whether MPs should be "delegates" or "trustees" – the "mandate-independence controversy" outlined by Pitkin (1967) – the references to their constituents and constituencies suggests AWS MPs shy away from the Burkean concept of trusteeship and see themselves more as strict representatives of their constituents. In Andeweg & Thomassen's (2005) typology of *ex ante*/*ex post* and above/below political representation, AWS MPs lean towards representation "from below", although their selection process is *ex ante*/*ex post*. AWS MPs also use events and individuals in their constituency as examples when speaking on a given topic (see the Appendix for more examples).

AWS MPs refer to their constituents both specifically and in the abstract, particularly when criticising government policy. For example, in debate on 4th March 2015, Gemma Doyle, than the Labour MP for West Dunbartonshire (elected on an AWS in 2010), when asked if she would give way to Conservative MP Stephen Mosley, responded:

> No, I will not [give way], because my constituents want me to make these points, not to give more time to Conservative Members.

On 2nd June 2010, during debate on Israel-Palestine, Valerie Vaz, MP for Walsall South, also used the views of her constituents to support her position:

> My constituents want more than pressure. Will the Foreign Secretary come back to the House and report on a timetable for the discussions on a diplomatic solution, just as we did on Ireland?

On 4th April 2001, Betty Williams, member for Conwy from 1997–2010, raised the case of a wilderness guide in her constituency unable to access parts of the countryside due to foot and mouth disease:

> Is my right hon. Friend aware that there is continuing concern about the limited access to the countryside and crags of north Wales? May I draw his attention to the circumstances of my constituent, Ric Potter? Like many others, he has had to travel to Scotland, where there is greater access. Will my right hon. Friend help us to enable people such as Ric Potter to find work in outdoor pursuits?

5 Appendix

5.1 Gender effect estimates

Estimate effects of different topics, using only gender.

Table 13: Topic Estimates

	Estimate	Standard Error	t value	Pr(>|t|)	
Topic 1 – Employment & unions					
1	Intercept	0.0120561	0.0001233	97.7458509	< 0.001 ***
1	Female	-0.0009786	0.0002204	-4.4396315	< 0.001 ***
Topic 2 – Legal system					
2	Intercept	0.0167102	0.0001677	99.6358100	< 0.001 ***
2	Female	0.0001861	0.0002867	0.6492618	0.52
Topic 3 – Roads					
3	Intercept	0.0116864	0.0001469	79.5274864	< 0.001 ***
3	Female	-0.0018110	0.0002574	-7.0349793	< 0.001 ***
Topic 4 – Housing					
4	Intercept	0.0112593	0.0001746	64.4711132	< 0.001 ***
4	Female	0.0054870	0.0002870	19.1204992	< 0.001 ***
Topic 5 – Police, firefighters & prison					
5	Intercept	0.0140238	0.0001747	80.2546259	< 0.001 ***
5	Female	0.0008970	0.0002998	2.9917221	0.003 **
Topic 6 – Northern Ireland					
6	Intercept	0.0089592	0.0000450	198.8903532	< 0.001 ***
6	Female	-0.0002231	0.0000821	-2.7163043	0.007 **
Topic 7 – Committee					
7	Intercept	0.0213132	0.0001509	141.2139750	< 0.001 ***
7	Female	-0.0015245	0.0002307	-6.6073185	< 0.001 ***
Topic 8 – Schools					
8	Intercept	0.0147366	0.0001975	74.6029960	< 0.001 ***
8	Female	0.0009898	0.0003519	2.8128100	0.005 **
Topic 9 – Energy & climate change					
9	Intercept	0.0170286	0.0002027	84.0111642	< 0.001 ***
9	Female	-0.0026669	0.0003638	-7.3306532	< 0.001 ***
Topic 10 – Defence					
10	Intercept	0.0157819	0.0001837	85.9128350	< 0.001 ***
10	Female	-0.0061172	0.0003240	-18.8794191	< 0.001 ***
Topic 11 – Parliament					
11	Intercept	0.0119042	0.0000790	150.6173576	< 0.001 ***
11	Female	-0.0019543	0.0001429	-13.6787831	< 0.001 ***
Topic 12 – International politics					
12	Intercept	0.0125948	0.0001249	100.8499998	< 0.001 ***
12	Female	-0.0050786	0.0002170	-23.4024173	< 0.001 ***
Topic 13 – Ministers					
13	Intercept	0.0167087	0.0001064	157.0415815	< 0.001 ***
13	Female	0.0011454	0.0001923	5.9551523	< 0.001 ***
Topic 14 – Policy impact					

Table 13: Topic Estimates *(continued)*

	Estimate	Standard Error	t value	Pr(>|t|)	
14	Intercept	0.0115397	0.0000460	251.1090985	< 0.001 ***
14	Female	0.0009556	0.0000875	10.9167682	< 0.001 ***
Topic 15 – Gender					
15	Intercept	0.0048738	0.0001146	42.5372998	< 0.001 ***
15	Female	0.0121863	0.0002379	51.2176906	< 0.001 ***
Topic 16 – Regional development					
16	Intercept	0.0230313	0.0001276	180.4911579	< 0.001 ***
16	Female	0.0026193	0.0002503	10.4645867	< 0.001 ***
Topic 17 – Communications					
17	Intercept	0.0097462	0.0001202	81.0915937	< 0.001 ***
17	Female	-0.0009899	0.0002069	-4.7848162	< 0.001 ***
Topic 18 – Immigration					
18	Intercept	0.0087105	0.0000900	96.8147319	< 0.001 ***
18	Female	-0.0000391	0.0001635	-0.2394474	0.81
Topic 19 – Health system					
19	Intercept	0.0161788	0.0001976	81.8627819	< 0.001 ***
19	Female	0.0079743	0.0003600	22.1488945	< 0.001 ***
Topic 20 – International development					
20	Intercept	0.0160465	0.0001897	84.5865773	< 0.001 ***
20	Female	-0.0020679	0.0003358	-6.1579789	< 0.001 ***
Topic 21 – Benefits & disability					
21	Intercept	0.0120722	0.0001441	83.8028248	< 0.001 ***
21	Female	0.0080944	0.0002832	28.5770350	< 0.001 ***
Topic 22 – Sport & culture					
22	Intercept	0.0127412	0.0001526	83.4724542	< 0.001 ***
22	Female	-0.0003753	0.0002649	-1.4166824	0.16
Topic 23 – History					
23	Intercept	0.0137581	0.0001117	123.2082084	< 0.001 ***
23	Female	-0.0046801	0.0001833	-25.5317143	< 0.001 ***
Topic 24 – Higher education & skills					
24	Intercept	0.0143325	0.0001641	87.3629912	< 0.001 ***
24	Female	-0.0004494	0.0003006	-1.4950418	0.13
Topic 25 – Concurring point					
25	Intercept	0.0155213	0.0000474	327.6313660	< 0.001 ***
25	Female	-0.0026315	0.0000760	-34.6035104	< 0.001 ***
Topic 26 – Pensions					
26	Intercept	0.0147019	0.0001709	86.0482540	< 0.001 ***
26	Female	0.0019874	0.0002808	7.0777074	< 0.001 ***
Topic 27 – Points of order					
27	Intercept	0.0177894	0.0001316	135.2139528	< 0.001 ***
27	Female	-0.0054025	0.0002166	-24.9447457	< 0.001 ***
Topic 28 – Issues					
28	Intercept	0.0345025	0.0000980	352.1646087	< 0.001 ***
28	Female	0.0006780	0.0001716	3.9511379	< 0.001 ***
Topic 29 – Constituencies					
29	Intercept	0.0131800	0.0000540	244.1589822	< 0.001 ***

Table 13: Topic Estimates *(continued)*

		Estimate	Standard Error	t value	Pr(>|t|)
29	Female	0.0023276	0.0001069	21.7824341	< 0.001 ***
Topic 30 – Ethnic groups & racism					
30	Intercept	0.0085781	0.0000728	117.8578866	< 0.001 ***
30	Female	0.0019552	0.0001365	14.3196680	< 0.001 ***
Topic 31 – Amendments					
31	Intercept	0.0150304	0.0001578	95.2713075	< 0.001 ***
31	Female	-0.0028669	0.0002705	-10.5980156	< 0.001 ***
Topic 32 – Reports					
32	Intercept	0.0169724	0.0001117	151.9867135	< 0.001 ***
32	Female	0.0012779	0.0001865	6.8516021	< 0.001 ***
Topic 33 – People					
33	Intercept	0.0377446	0.0001213	311.2792086	< 0.001 ***
33	Female	-0.0014521	0.0002123	-6.8400753	< 0.001 ***
Topic 34 – Wales & Scotland					
34	Intercept	0.0135410	0.0001549	87.4194387	< 0.001 ***
34	Female	-0.0031743	0.0002506	-12.6669967	< 0.001 ***
Topic 35 – Alcohol & tobacco					
35	Intercept	0.0108579	0.0001486	73.0683773	< 0.001 ***
35	Female	0.0005320	0.0002832	1.8786468	0.060
Topic 36 – Place names					
36	Intercept	0.0083659	0.0000671	124.6776088	< 0.001 ***
36	Female	0.0007972	0.0001241	6.4237856	< 0.001 ***
Topic 37 – Budget					
37	Intercept	0.0246505	0.0001775	138.8996009	< 0.001 ***
37	Female	-0.0003435	0.0002961	-1.1599722	0.25
Topic 38 – Tax					
38	Intercept	0.0193082	0.0001896	101.8596764	< 0.001 ***
38	Female	0.0030544	0.0003310	9.2272811	< 0.001 ***
Topic 39 – Private companies					
39	Intercept	0.0123871	0.0001199	103.3046194	< 0.001 ***
39	Female	-0.0009559	0.0002220	-4.3062780	< 0.001 ***
Topic 40 – Environment & fishing					
40	Intercept	0.0094757	0.0001428	66.3605526	< 0.001 ***
40	Female	-0.0024801	0.0002435	-10.1854049	< 0.001 ***
Topic 41 – Crime					
41	Intercept	0.0141387	0.0001700	83.1774783	< 0.001 ***
41	Female	0.0052430	0.0003115	16.8290865	< 0.001 ***
Topic 42 – Bills					
42	Intercept	0.0244386	0.0001508	162.0410131	< 0.001 ***
42	Female	-0.0012130	0.0002557	-4.7439287	< 0.001 ***
Topic 43 – Children					
43	Intercept	0.0076822	0.0001213	63.3511535	< 0.001 ***
43	Female	0.0094502	0.0002461	38.3935766	< 0.001 ***
Topic 44 – Utilities & PFI					
44	Intercept	0.0123659	0.0000838	147.6006401	< 0.001 ***
44	Female	-0.0001325	0.0001597	-0.8294008	0.41

Table 13: Topic Estimates *(continued)*

		Estimate	Standard Error	t value	Pr(>|t|)
Topic 45 – Middle East					
45	Intercept	0.0174606	0.0002080	83.9606437	< 0.001 ***
45	Female	-0.0020795	0.0003607	-5.7649929	< 0.001 ***
Topic 46 – Local authorities					
46	Intercept	0.0179838	0.0001437	125.1849736	< 0.001 ***
46	Female	0.0015586	0.0002836	5.4965933	< 0.001 ***
Topic 47 – Elections					
47	Intercept	0.0181834	0.0001549	117.3877176	< 0.001 ***
47	Female	-0.0075879	0.0002715	-27.9430467	< 0.001 ***
Topic 48 – Debate					
48	Intercept	0.0180191	0.0000681	264.6774024	< 0.001 ***
48	Female	-0.0018256	0.0001238	-14.7506463	< 0.001 ***
Topic 49 – Transport					
49	Intercept	0.0163759	0.0001857	88.1991855	< 0.001 ***
49	Female	-0.0002969	0.0003477	-0.8538425	0.39
Topic 50 – Questions					
50	Intercept	0.0161647	0.0000757	213.4856091	< 0.001 ***
50	Female	0.0001682	0.0001301	1.2927442	0.20
Topic 51 – Families					
51	Intercept	0.0101120	0.0001164	86.8890866	< 0.001 ***
51	Female	0.0044922	0.0002501	17.9608814	< 0.001 ***
Topic 52 – Health research					
52	Intercept	0.0087873	0.0001603	54.8116345	< 0.001 ***
52	Female	0.0050129	0.0002923	17.1518648	< 0.001 ***
Topic 53 – Dispatch box					
53	Intercept	0.0075482	0.0000252	299.9335737	< 0.001 ***
53	Female	-0.0010058	0.0000411	-24.4759297	< 0.001 ***
Topic 54 – Parties					
54	Intercept	0.0248257	0.0001495	166.0099980	< 0.001 ***
54	Female	-0.0062183	0.0002451	-25.3739370	< 0.001 ***
Topic 55 – Statements					
55	Intercept	0.0211074	0.0000674	313.1127111	< 0.001 ***
55	Female	-0.0025215	0.0001226	-20.5654157	< 0.001 ***
Topic 56 – European Union					
56	Intercept	0.0163664	0.0001702	96.1683285	< 0.001 ***
56	Female	-0.0044278	0.0002939	-15.0664007	< 0.001 ***
Topic 57 – Locations					
57	Intercept	0.0100682	0.0001051	95.7956424	< 0.001 ***
57	Female	-0.0008438	0.0001896	-4.4503909	< 0.001 ***
Topic 58 – Jobs & manufacturing					
58	Intercept	0.0176030	0.0001701	103.4783706	< 0.001 ***
58	Female	0.0002215	0.0003125	0.7086483	0.48
Topic 59 – Small business					
59	Intercept	0.0070547	0.0000690	102.2200613	< 0.001 ***
59	Female	-0.0000227	0.0001167	-0.1948699	0.85
Topic 60 – Agreement & disagreement					

Table 13: Topic Estimates *(continued)*

	Estimate	Standard Error	t value	Pr(>|t|)	
60	Intercept	0.0328354	0.0001082	303.3701317	< 0.001 ***
60	Female	-0.0102158	0.0001823	-56.0338702	< 0.001 ***
Topic 61 – Voluntary sector					
61	Intercept	0.0187326	0.0001134	165.1455528	< 0.001 ***
61	Female	0.0075517	0.0002253	33.5146669	< 0.001 ***
Topic 62 – Comments					
62	Intercept	0.0152785	0.0000587	260.3794919	< 0.001 ***
62	Female	-0.0036504	0.0000997	-36.6196859	< 0.001 ***
Topic 63 – Social care					
63	Intercept	0.0090888	0.0001324	68.6336761	< 0.001 ***
63	Female	0.0080677	0.0002317	34.8179514	< 0.001 ***
Topic 64 – Time					
64	Intercept	0.0213910	0.0000681	314.0303987	< 0.001 ***
64	Female	-0.0017923	0.0001249	-14.3468017	< 0.001 ***
Topic 65 – Media & animals					
65	Intercept	0.0121571	0.0001637	74.2672732	< 0.001 ***
65	Female	-0.0030953	0.0002716	-11.3961506	< 0.001 ***
Topic 66 – Other					
66	Intercept	0.0038287	0.0000119	322.4905663	< 0.001 ***
66	Female	0.0002877	0.0000200	14.3849523	< 0.001 ***

5.2 θ distribution

Figure 17 shows the distribution of θ scores used to assign overall topics to individual speeches in Table 10, per topic.

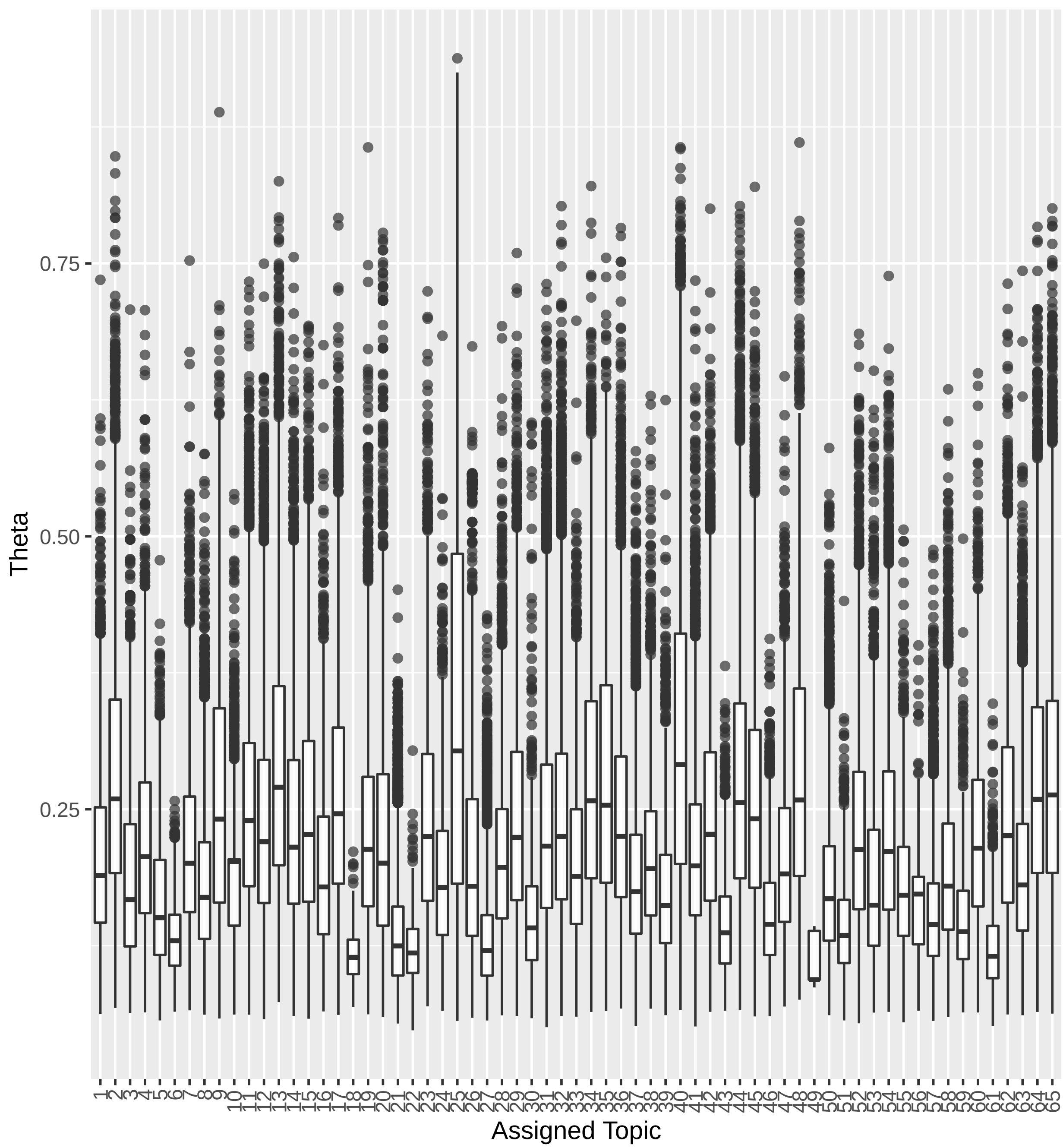

Figure 17: Theta Values in Topic Assignment

5.3 AWS References to Constituents in Context

A random selection of 2% of all references to “my constituency”, “my constituent” and “my constituents”, by AWS MPs, in context.

Table 14: A random sample of KWIC's

Pre	Keyword	Post
. I was briefed by a vehicle hire company in	my constituency	called Reflex and, quite frankly, if such banking
150 per cent. two years ago. Another of	my constituents	has advised me of an application for an 85 per
already begun, for example just over the border from	my constituency	in the constituency of my hon. Friend the Member
in which Cornish children study. Three secondary schools in	my constituency	will be located on the same site, and one
Manchester has been doing a major infrastructure project, and	my constituents	are at the end of their tether about the lack
patient at the BRI, and Airedale hospital is in	my constituency	. The hon. Member for South Cambridgeshire Mr.
, but the reality is there to be seen in	my constituency	. On Saturday I met a delegation of workers from
to use their abilities and develop their talents. In	my constituency	, 366 young people who have been unemployed for more
I believe that the most effective electoral registration officer in	my constituency	is mum. It is mum who fills in the
can arise from defective gas appliances, because two of	my constituents	, young students in their 20s, died from carbon
£ 3.6 million. Some 9% of people in	my constituency	are hard-working, entrepreneurial self-employed people, and today is
my right hon. Friend congratulate Aldercar community school in	my constituency	and its staff and pupils? The percentage of pupils
", One particular concern for many of	my constituents	is bus fares. As I have said, my
, Jobs and employment are the biggest issue in	my constituency	and the latest figures now show that just under 2,000
otherwise reach. The Psychiatric Rehabilitation Association is based in	my constituency	and was set up in 1959-it is no coincidence that
financial inclusion fund. Where would the Minister suggest that	my constituents	who are struggling with debt and excessive and escalating charges
and without the full participation of the British people,	my constituents	and the country will never forgive them.
. There is an additional problem that is relevant to	my constituency	. It contains a large outdoor venue called the National
if they continue to propose new services that, in	my constituents	' view, favour the administration of the hospital or
in red tape. That will be a turn-off.	My constituency	and the town in which it is situated has a
With my right hon. Friend's local knowledge of	my constituency	, she will know that many of my constituents are
", to close a wide range of services at	my constituency's	local hospital, St Helier. Most of the controversy
I am extremely worried for	my constituents	in Ashton-under-Lyne, Droylsden and Failsworth, and for people
One of the shortlisted sites is at Barnard Castle in	my constituency	, and that would produce 1,000 jobs.

Table 14: A random sample of KWIC's *(continued)*

Pre	Keyword	Post
making ends meet has been raised with me repeatedly by	my constituents	, including Graeme McGrory, who cares for his partner
One piece of transport infrastructure that	my constituency	and that of the hon. Member for Buckingham John
A director of Sirus Automotive who lives in	my constituency	would like to take on apprentices, but he has
" Three people who know that better than most are	my constituents	Mark, Joanne and Ben King. In 2011,
There are 3,540 women affected by the changes in	my constituency	. Does my hon. Friend agree that the 1995
have been down in the detail of rail provision in	my constituency	, but these are important matters for many of those
just a few examples of the work being done in	my constituency	. I recently had the privilege of accompanying the Gateshead
, but that does not help the large number of	my constituents	who have lost some, if not all, of
was the only mainstream candidate in the general election in	my constituency	who did not have their picture taken while pointing to
was not even in the mortgage application, NatWest told	my constituents	that it was in the process of adding it.
is a measure of the Government's achievement that people in	my constituency	and elsewhere in Northamptonshire can look forward to a secure
clothing company announced the closure of two more factories in	my constituency	and the neighbouring Erewash constituency. A huge number of
my primary care trust in north-east Derbyshire and dentists in	my constituency	to find a local solution. These reforms coincide with
Cross, just a few miles up the road from	my constituency	. That pipe manufacturing works has been taken over by
go ahead. There is huge concern about this in	my constituency	and across the north. Was the Prime Minister told
backgrounds, including poor backgrounds, and is representative of	my constituency	. That is the sort of school that Labour Members
are subject to a TPIM. This information would let	my constituents	know whether potential terrorism suspects had returned to London.
. Gentleman for his generosity. Is he aware that	my constituency	is probably the one with the highest number of gas
because I have had direct experience of the issue in	my constituency	. A woman came over here as the wife of
. Let us take the feed-in tariff fiasco. In	my constituency	alone, we are losing many jobs, because a
What practical advice can the Secretary of State give to	my constituents	, as some 3,000 householders in my constituency face a
sport, that this is good enough for kids in	my constituency	?
a fair deal on jobs, getting young people in	my constituency	and others involved in working our way out of the
argument is best explained by reference to the case of	my constituent	, Neil Kenny, who raised his concerns about the

Table 14: A random sample of KWIC's *(continued)*

Pre	Keyword	Post
to LEAs give rise to some questions, including in	my constituency	from Unison, which is concerned that LEAs might use
Such travel will be available to all 17,600 pensioners in	my constituency	. , In February I visited
", What point is there in forcing	my constituent	who is a single dad who has his two children
replies, perhaps he can respond to the questions that	my constituent	has raised. What is she to do? She
ask my hon. Friend to offer an undertaking to	my constituents	in Mitcham and Morden that an option appraisal of intermediate
he would be interested to hear the Minister's response to	my constituent	Maureen Davenport. The Minister said that the maximum state
in child benefit, which will help 13,800 families in	my constituency	. My real reason for tabling the question is to
Finchley and Golders Green Mike Freer), many of	my constituents	killed by lorries have died at junctions, including some
Hall the plight of former United Engineering Forgings workers in	my constituency	who will not receive the returns from their final salary
London has had Oyster cards for nine years, but	my constituents	are still waiting. Although Transport for Greater Manchester is
again have a university. However, Nene college in	my constituency	hopes to change all that, and I support strongly
Enforcement Campaign-in Cardiff, and particularly to the work of	my constituent	, Professor John Shepherd, who works in the dental
and assets than non-disabled people. In London, where	my constituency	and the constituency of my hon. Friend the Member
in particular from the circumstances of students in Northampton.	My constituency	contains both a higher education and a further education college
the marine Bill on the grounds of its irrelevance to	my constituents	, because, like the hon. Lady, I
deepest concern for the families involved, especially given that	my constituency	neighbours that of my hon. Friend the Member for
services can expand on the slow line so that all	my constituents	benefit from the west coast main line upgrade?
rehabilitation. , The people of	my constituency	have been horrified by those cases, and it is
Labour Government we have achieved a tremendous amount. In	my constituency	the number of people claiming jobseeker's allowance has almost halved
they complain? Where will the local accountability go?	My constituents	very much value the highly accessible local service that they
", Since helping the Jarrow marchers,	my constituency	has continued to welcome people from throughout the UK,
and not-for-profit groups, of which there are many in	my constituency	, doing immensely valuable work. They all too often
as soon as possible. Indeed, for some of	my constituents	, reform is already coming too late.

Table 14: A random sample of KWIC's *(continued)*

Pre	Keyword	Post
bus travel in Wales. I have met pensioners in	my constituency	who say that it has transformed their lives. As
and Sir Malcolm Thornton. All have represented part of	my constituency	and all left this House on 20 April or 1
Ports is the operator at the port of Immingham in	my constituency	. The companies there firmly believe that they have paid
Conservative-controlled Bradford city council excluded the wonderful Ilkley lido in	my constituency	from the free swimming initiative for young people and pensioners
for my hon. Friend's reply, and many of	my constituents	who have come across the benefit integrity project will be
Tero was not properly treated and offer the apology that	my constituent	deserves.
about their corporate social responsibilities. For the sake of	my constituents	in Mitcham, Morden and Colliers Wood who want something
change in the law. Regrettably, not only in	my constituency	but in many northern towns and cities, I see
on an issue that has been of great concern to	my constituents	. While I appreciate the cross-party consensus that exists on
In	my constituency	of West Lancashire, the national lottery has supported 266
to meet the skills gap in engineering and construction in	my constituency	. , When I talk to
sat with the parents of the two children who were	my constituents	, as has Ken Livingstone, who made a private
who have been strongly encouraged to save The consultation in	my constituency	on the pensioners tax credit was extremely successful. The
Government for investing in the city of Bradford, helping	my constituents	to realise their potential. But in reality little has
visited Dot To Dot, a community arts project in	my constituency	. It has a good record of involving the community
one regret the fact that Westminster, which covers half	my constituency	, has so far concentrated CCTV bids-I am sure with
also significant gaps in the Bill. One example from	my constituency	concerns a community hydro project in Saddleworth that might not
hon. Friend for that reply, but most of	my constituents	probably do not know what a low carbon transition plan
has provided opportunities where there were none before. In	my constituency	, there have been far more opportunities in the past
to find examples of such practices. Another case in	my constituency	, with which I am dealing, involves elderly victims
. , The credit union in	my constituency	is fragile, because it serves an area in which
certainly applies to me because the acute trust that covers	my constituents	, who desperately need care, has the mother and
reveal a trend, and I see it happening in	my constituency	. It is a demonstrable fact that the polarisation between
	My constituent	, John Warren, has specifically asked me to raise

Table 14: A random sample of KWIC's *(continued)*

Pre	Keyword	Post
, Bridges Project in Musselburgh in	my constituency	does a brilliant job in supporting young people. A
Spowart, a small firm of legal aid solicitors in	my constituency	. Solicitors at the firm are paid generally between £
, both as a national concern and as it affects	my constituency	. I am grateful to my hon. Friend for
, nor, sadly, are far too many of	my constituents	.
	My constituents	in Hull are baffled by the Government's approach. At
issue and go after these criminals who are preying on	my constituents	?
even begin for another 12 months. Young people in	my constituency	should not have to spend another year on the dole
with the nutrition they need outside term time. In	my constituency	, several schools run summer programmes funded through the pupil
takes umbrage at being forced to do repairs-as some of	my constituents	, sadly, know to their cost.
", I recently visited a care home in	my constituency	that is provided by a small charity and is rated
House and members of the armed forces, such as	my constituent	, 19-year-old Private James Kenny of C company, 3rd
as out to Kent. There are seven stations in	my constituency	: Hither Green, Blackheath, Lee, Grove Park
Can my right hon. Friend give any assurance to	my constituent	, Mr. Peter Dyson, who has written to
Commons Library to conduct an analysis of the impact in	my constituency	. I discovered that 4,300 women and 3,800 men would
100 days of the new Parliament? Many businesses in	my constituency	are struggling significantly and would undoubtedly welcome a period of
in 1992, as the Member for Woolwich, before	my constituency	was formed for the 1997 election. John Austin is
were building up and seemed to take action only once	my constituents	had suffered a very high level of nuisance and there
that further education institutions, such as Blackburn College in	my constituency	, will not receive a real-terms funding cut as a
", On a more serious note,	my constituency	is home to manufacturers varying from Corus to Cadbury,
costs and cuts to working tax credits, families in	my constituency	will be worse off. I will not vote in
be warm. It paid for basics like that in	my constituency	. I will not revisit the pain of tuition fees
is a national issue. The 900 steel workers in	my constituency	whose jobs are on the line expect him to guarantee
to begin by speaking about the NHS as experienced by	my constituents	. Getting an appointment to see a GP can be
I was struck by what one of	my constituents	said last weekend, which was that the attacks that
", On 18 February, Llandudno in	my constituency	hosted the first North Wales criminal justice board conference.

Table 14: A random sample of KWIC's *(continued)*

Pre	Keyword	Post
my hon. Friend foresee for the young people in	my constituency	if they are to suffer possible cuts alongside that idiosyncratic
busways and widen the M1. Is he aware that	my constituency	will have the new Translink guided busway by 2008 due
" Last week, I hosted a jobs fair in	my constituency	, as have many hon. Members on both sides
in the south-east will be dealt with in Parliament?	My constituents	want to know where we are going and what the
him to visit the brand-new children's centre in Elland in	my constituency	, which is due to open in January, and
realities for people affected by this situation. One of	my constituents	is stuck out in Saudi Arabia. His work has
the past few days. When the problems started in	my constituency	on Monday night, we saw copycat criminality, mindless
those branches, in Catford and Blackheath, are in	my constituency	and two others, in Lewisham and Greenwich, are
	My constituent	, Richard Belmar, has now spent nearly three years
Postwatch because I am unhappy about the consultation process in	my constituency	. I fully accept many of my hon. Friend's
area of Keighley last Friday and talking to many of	my constituents	and taking on board many of their anxieties. On
of the major issues raised with me by carers in	my constituency	. We must take such issues on board.\
that the voucher company Farepak, which is based in	my constituency	, collapsed this week, robbing thousands of people on
scientific reports recommend restricted phone use by younger children.	My constituents	do not believe that such recommendations tally with the telecommunications
. Mullin). This is a big issue in	my constituency	, where inappropriate development on garden sites is taking place
scrutiny process, but it is impossible for me,	my constituents	or councillors of any party not involved in that enterprise
", At the time, I was consulting	my constituents	about their attitudes to crime and antisocial behaviour, and
you prove it? ,	My constituency	is served by two hospitals: Dewsbury and District hospital
% reduction. What reassurances can the Minister give to	my constituents	and firefighters that those latest cuts will not jeopardise or
. , Horwich visiting service in	my constituency	has lost funding and can no longer employ its part-time
I have spoken to many businesses in	my constituency	. Will the hon. Gentleman concede that the Government's
prevent businesses from going into administration, as many in	my constituency	are likely to do. Finally, the local authority
I do not know whether my experience in	my constituency	has been exactly the same as that of my right
? , Many SMEs operate in	my constituency	, and I want to ensure that the skills base
that population live in Salford, the local authority for	my constituency	. , In last year's debate

Table 14: A random sample of KWIC's *(continued)*

Pre	Keyword	Post
It is an issue that has been simmering away in	my constituency	and recently the rumours have turned to reality as the
of the parenting lessons that go on in schools in	my constituency	to great effect. The hon. Gentleman ignores those
a distraught couple who run a hedgehog rescue centre in	my constituency	. They are currently nursing back to health a hedgehog
people to think that that was the total sum of	my constituency	. It is an extremely nice place to spend Christmas
transparency about the impact. ,	My constituents	are also anxious about the Government's proposals to allow fracking
some of its provisions will have on vulnerable people in	my constituency	. , I shall first raise
key elements of creative business growth. Creative businesses in	my constituency	and in a large area to the west of London
In Pembrokeshire we have two oil refineries, one in	my constituency	. They were both affected by the blockades in September
thank the Minister for his reply. Head teachers in	my constituency	are concerned that Government have still not come forward with
the work of local authorities in my area. In	my constituency	, there are no high profile arts venues that hit
many of the early asbestosis claims from Hebden Bridge in	my constituency	might not have succeeded under the proposed 75 per cent
job first.\ ,	My constituency	is pronounced\ Erreywash\ , not\
that is not regulated properly, with the result that	my constituents	, who have small sums of money available to invest
a picture of the winning design, but people in	my constituency	have seen many pictures before. I want work to
hour. I have written to all the headteachers in	my constituency	over the last few weeks, and they tell me
this debate falls on an anniversary well worth remembering for	my constituents	. It is 20 years to the month that post-war
people of the east end, including the people of	my constituency	, talk to me about how excited they still are
I recently visited Bishop Barrington school in	my constituency	, which has got a new science lab and sports
the extent of the disruption and the problems caused for	my constituents	? I would be happy to do that.\
increase in the number of new homes being built in	my constituency	over the past 10 years or so. For the
junior doctors who are the problem, but him?	My constituents-hundreds	of whom have written to me-overwhelmingly feel that he has
, , I do not think	my constituents	knew whether to laugh or cry.
about to be built in Walkden in the centre of	my constituency	. The new local improvement finance trust-LIFT-centre will include GP
is higher, and the dole queue is lengthening.	My constituents	are only too well aware of the exploitative practices of
" I am fortunate in having a research centre in	my constituency	at the university of Durham, which concentrates on enabling

Table 14: A random sample of KWIC's *(continued)*

Pre	Keyword	Post
is talking about the wrong hospital, which many of	my constituents	will find most amusing.
of the Land Registry would be bad not just for	my constituents	but for the public as a whole. The revenue
The food banks in	my constituency	, which currently number at least six, tell me
of those issues. , In	my constituency	, the credit union benefits from capital and revenue from
children. I am indebted to a law company in	my constituency	called Just for Kids Law, which has raised with
hope they are not giving false hope to many of	my constituents	. Will they just admit that they have made a
I have a range of energy-intensive industries in	my constituency	, including steel, glass, paper and the entire
the save Lewisham hospital campaign. But for now,	my constituents	still face the prospect of seriously downgraded services at their
from and bugbear for my constituents. On behalf of	my constituents	and their families, I very much look forward to
", helped motorists and the hard-pressed hauliers in	my constituency-or	they could have looked at jobs for young people.
Staff at Trinity, Bluecoat and Fernwood schools in	my constituency	are desperate for extra investment in their buildings. Will
The point about geography is critical in Cumbria, where	my constituency	is. Under the proposals, we will end up
will affect disabled youngsters. The What? centre in	my constituency	, which gives counselling to all youngsters, still does
closure of the offices is having a direct impact on	my constituency	. Walsall faces the closure of its HMRC office,
. , Frustration is evident among	my constituents	: for many years, they have felt marginalised and
, larger numbers of people are choosing to live in	my constituency	but work in London. If we are to take
ethnic minority children, of whom there are many in	my constituency	. , We have dealt a
single parents in the country-I will return to that point-and	my constituents	think that the measure is unfair. How people in
should not come back from our holidays to find that	my constituents	, and those of my neighbours, have lost their
their area; I fully intend to do so in	my constituency	. , We also need better
too much movement. I want Airedale general hospital in	my constituency	not just to survive, but to prosper. It
", During the summer and autumn months,	my constituents	and those of many other hon. Members were affected
put a human face on many of the difficulties that	my constituents	experience. , In Newham,
Parent Action Network, which has its national headquarters in	my constituency	. It has just received nearly £ 400,000 in lottery
sector. On Friday, an independent community pharmacist in	my constituency	told me that he estimated that the Government cuts would

Table 14: A random sample of KWIC's *(continued)*

Pre	Keyword	Post
it becomes an empty gesture. A community group in	my constituency	is setting up a community development trust, and it
since June and doubled since 2006. Young people in	my constituency	have been particularly badly hit, with a 288%
police get back to strength to defend the people in	my constituency	of Mitcham and Morden?
to address have been influenced by what has happened in	my constituency	in the past 10 days as a series of incidents
, including those of Allied Steel and Wire's pensioners in	my constituency	? They took the case to court through the unions
Indeed, it is a stealth cut. In	my constituency	, the Tories will have to make stealth cuts such
communities across the UK. I understand the concerns of	my constituents	. I understand that when a family from a different
a vested interest in ensuring the safety and security of	my constituency	, which in the past has been a military target
infrastructure project is a massive economic opportunity for Wales and	my constituency	in particular. Will the Minister assure the House that
Nottingham that stands to lose most is the Meadows in	my constituency	. Before the last election, the Meadows, one
am here this afternoon specifically to represent the concerns of	my constituents	who are trade union members in Parliament, as they
. Nothing could be further from the truth, as	my constituency	exemplifies. As I have already said, I represent
making are the very ones that have been made by	my constituents	, by the constituents of my hon. Friends and-I
, but wanted to take the opportunity to read out	my constituent's	comments so that Ministers understand the worry and concern.
firm of Hickman and Rose, which is based in	my constituency	? She was due to speak at a conference organised
Majesty's Opposition. That public money could be used for	my constituent	Grace Ryder, aged 9, who was recently diagnosed
changes that will affect 650 families and 1,500 children in	my constituency	. , These are ideologically driven
deal more about the birdlife in both estuaries that surround	my constituency	. , The Bill establishes a
	My constituent	, the wonderful campaigner Marie Lyons, has doggedly pursued
\ vote for their Muslim brother\ .	My constituents	were told that that was their religious duty. When
. It will bring huge benefits to many families in	my constituency	who are on low or not very generous incomes.
anywhere. , The diversity of	my constituency	is one of the reasons why it is the best
c The NHS in	my constituency	has moved beyond special measures into the success regime.
invited my right hon. and learned Friend to meet	my constituents	to hear what they think about our local NHS.

Table 14: A random sample of KWIC's *(continued)*

Pre	Keyword	Post
fleeing Ebola-affected countries are not left destitute and homeless?	My constituents	, Mr and Mrs Mahmood, have been working in
pension credit, but I wondered whether Ministers could give	my constituent	and me advice on whether the notional sum tied up
first home. There are so many young people in	my constituency	who see homes priced out of their reach and for
There are also problems for low-income families, such as	my constituent	on Colleymoor Leys lane who says:
term. I know from the experience of businesses in	my constituency	and in the surrounding west midlands area that New Street
that he needs those, but he failed to tell	my constituents	watching yesterday that a 1p cut in duty will not
average, which show that over a fifth-22% in	my constituency-of	people who resort to food banks for an emergency food

References

Airoldi, E. M., & Bischof, J. M. (2016). Improving and Evaluating Topic Models and Other Models of Text. *Journal of the American Statistical Association*, *111*(516), 1381–1403. https://doi.org/10.1080/01621459.2015.1051182

Andeweg, R. B., & Thomassen, J. J. (2005). Modes of Political Representation: Toward a New Typology. *Legislative Studies Quarterly*, *30*(4), 507–528. https://doi.org/10.3162/036298005X201653

Arora, S., Ge, R., Halpern, Y., Mimno, D., Moitra, A., Sontag, D., … Zhu, M. (2013). A Practical Algorithm for Topic Modeling with Provable Guarantees. In S. Dasgupta & D. McAllester (Eds.), *Proceedings of the 30th International Conference on Machine Learning* (Vol. 28, pp. 280–288). Atlanta, Georgia, USA: PMLR. Retrieved from http://proceedings.mlr.press/v28/arora13.pdf

Audickas, L., Hawkins, O., & Cracknell, R. (2017). *UK Election Statistics: 1918-2017* (Briefing Paper No. CBP7529) (p. 89). London: House of Commons Library. Retrieved from http://researchbriefings.parliament.uk/ResearchBriefing/Summary/CBP-7529

Benoit, K. (2018). *Quanteda: Quantitative Analysis of Textual Data*. https://doi.org/10.5281/zenodo.1004683

Benoit, K., & Matsuo, A. (2018). *Spacyr: Wrapper to the 'spaCy' 'NLP' Library*. Retrieved from http://github.com/quanteda/spacyr

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, *3*(Jan), 993–1022.

Bligh, M., Merolla, J., Schroedel, J. R., & Gonzalez, R. (2010). Finding Her Voice: Hillary Clinton's Rhetoric in the 2008 Presidential Campaign. *Women's Studies*, *39*(8), 823–850. https://doi.org/10.1080/00497878.2010.513316

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed). Hillsdale, N.J: L. Erlbaum Associates.

Fruchterman, T. M. J., & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software: Practice and Experience*, *21*(11), 1129–1164. https://doi.org/10.1002/spe.4380211102

Gagolewski, M. (2018). R package stringi: Character string processing facilities. https://doi.org/10.5281/zenodo.1292492

Grimmer, J., & Stewart, B. M. (2013). Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts. *Political Analysis*, *21*(03), 267–297. https://doi.org/10.1093/pan/mps028

Honnibal, M., & Montani, I. (2017). spaCy 2: Natural language understanding with Bloom embeddings, convolutional neural networks and incremental parsing. *To Appear*. Retrieved from https://spacy.io

Jones, J. J. (2016). Talk "Like a Man": The Linguistic Styles of Hillary Clinton, 1992-2013. *Perspectives on Politics*, *14*(03), 625–642. https://doi.org/10.1017/S1537592716001092

Kelly, R., & White, I. (2016). *All-women shortlists* (Briefing Paper No. 5057) (p. 34). London: House of Commons Library. Retrieved from https://researchbriefings.parliament.uk/ResearchBriefing/Summary/SN05057

Kincaid, J. P., Fishburne, R. P., Rogers, R. L., & Chissom, B. S. (1975). *Derivation of New Readability Formulas (Automated Readability Index, Fog Count and Flesch Reading Ease Formula) for Navy Enlisted Personnel:* Fort Belvoir, VA: Defense Technical Information Center. https://doi.org/10.21236/ADA006655

Lee, M., & Mimno, D. (2014). Low-dimensional Embeddings for Interpretable Anchor-based Topic Inference. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)* (pp. 1319–1328). Doha, Qatar: Association for Computational Linguistics. https://doi.org/10.3115/v1/D14-1138

Mimno, D., Wallach, H. M., Talley, E., Leenders, M., & McCallum, A. (2011). Optimizing semantic coherence in topic models. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing* (pp. 262–272). Edinburgh: Association for Computational Linguistics. Retrieved from https://dl.acm.org/citation.cfm?id=2145432.2145462

Newman, M. L., Groom, C. J., Handelman, L. D., & Pennebaker, J. W. (2008). Gender Differences in Language Use: An Analysis of 14,000 Text Samples. *Discourse Processes*, *45*(3), 211–236. https://doi.org/10.1080/01638530802073712

Odell, E. (2018). Hansard Speeches and Sentiment V2.5.1 [dataset]. https://doi.org/10.5281/zenodo.1306964

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). The Development and Psychometric Properties of LIWC2015, 26. Retrieved from https://repositories.lib.utexas.edu/bitstream/handle/2152/31333/LIWC2015_LanguageManual.pdf

Pitkin, H. F. (1967). *The concept of representation* (1. paperback ed., [Nachdr.]). Berkeley, Calif.: Univ. of California Press.

Quinn, K. M., Monroe, B. L., Colaresi, M., Crespin, M. H., & Radev, D. R. (2010). How to Analyze Political Attention with Minimal Assumptions and Costs. *American Journal of Political Science*, *54*(1), 209–228. https://doi.org/10.1111/j.1540-5907.2009.00427.x

Roberts, M. E., Stewart, B. M., & Airoldi, E. M. (2016). A Model of Text for Experimentation in the Social Sciences. *Journal of the American Statistical Association*, *111*(515), 988–1003. https://doi.org/10.1080/01621459.2016.1141684

Roberts, M. E., Stewart, B. M., & Tingley, D. (2018). *Stm: R Package for Structural Topic Models*. Retrieved from http://www.structuraltopicmodel.com

Taddy, M. A. (2012). On Estimation and Selection for Topic Models. In *Proceedings of the 15th International Conference on Artificial Intelligence and Statistics* (Vol. 22, pp. 1184–1193). La Palma, Canary Island: JMLR W&CP.

Yu, B. (2014). Language and gender in Congressional speech. *Literary and Linguistic Computing*, *29*(1), 118–132. https://doi.org/10.1093/llc/fqs073