

All Women Shortlists Methodology

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1 Descriptive Statistics

Data in Table 1 is from House of Commons Library reports (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: Number of Speeches and Words in Dataset

Gender	Speeches	Words
All	1,101	139,679
All	657,513	111,320,077
Female	149,799	26,369,159
Conservatives		
Female	1,055	128,958
All Women Shortlists	42	9,167
Male	507,714	84,950,918
Labour		
Male	4	1,554
All	285,291	44,800,169
Female	48,768	7,363,031
Male	236,523	37,437,138
All	261,942	46,494,850
Liberal Democrat		
Female	84,569	15,897,929
Non-All Women Shortlists	28,651	5,415,005
All Women Shortlists	55,918	10,482,924
Other		
Male	177,373	30,596,921
All	72,716	13,485,902
Female	7,552	1,503,459
Male	65,164	11,982,443
All	36,463	6,399,477
Female	7,813	1,466,615
Male	28,650	4,932,862

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 were 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.

2.1 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 were calculated using **stringi** (Gagolewski, 2018), a wrapper to the ICU regex library.

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

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

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

- Words longer than six letters (Sixltr)

We also included mean words-per-sentence (WPS), total speech word count (WC) and Flesch–Kincaid grade level (FK) (Kincaid, Fishburne, Rogers, & Chissom, 1975), calculated using **Quanteda** (Benoit, 2018) and **stringi** (Gagolewski, 2018).

2.1.1 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 – exceeded the $|0.1|$ threshold suggested by Newman et al (2008).

2.1.2 Shortlists vs Non-Shortlists

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

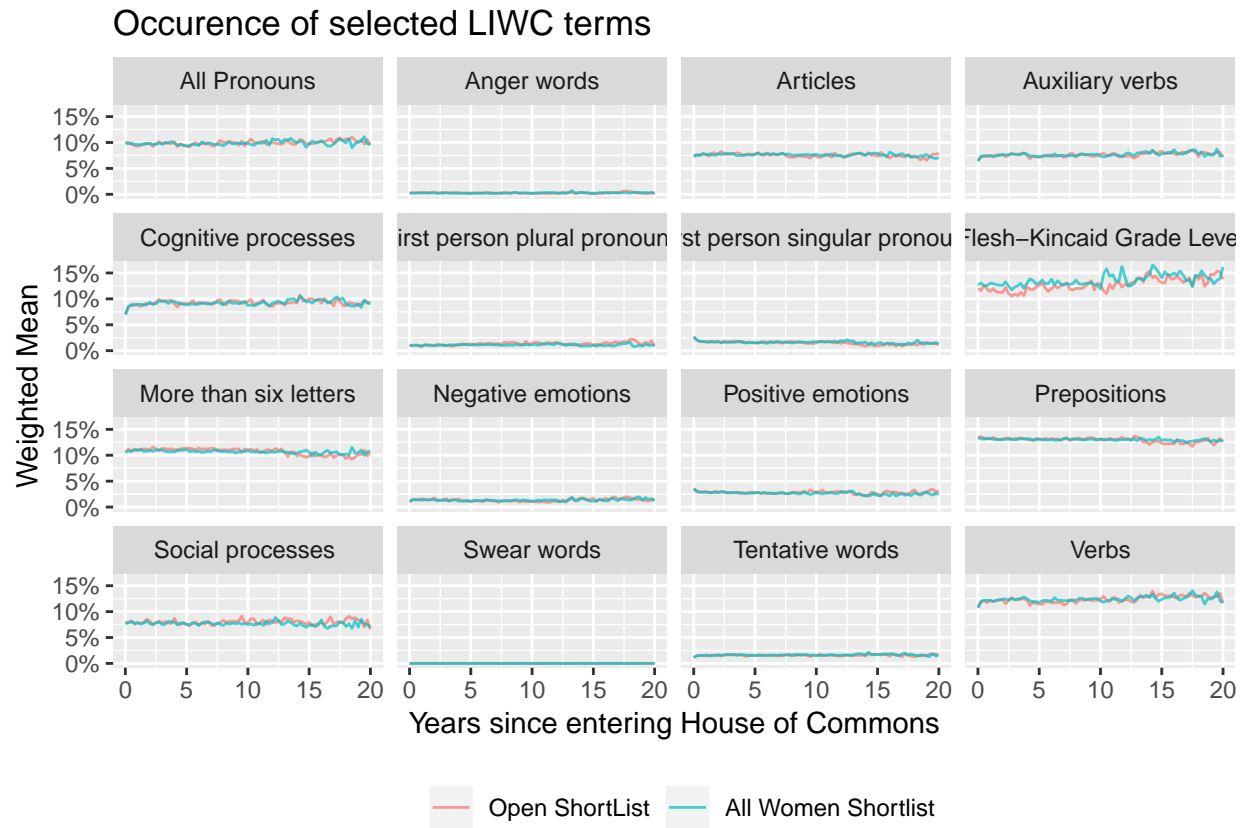


Figure 1: Occurence of selected LIWC terms

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 $|0.1|$.

2.1.3 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, like inter-Labour differences.

2.1.4 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	1	1	1	1	1	1
First person singular pronouns	2	2	2	2	2	2
First person plural pronouns	3	3	3	3	3	3
Verbs	4	4	4	4	4	4
Auxiliary verbs	5	5	5	5	5	5
Social processes	6	6	6	6	6	6
Positive emotions	7	7	7	7	7	7
Negative emotions	8	8	8	8	8	8
Tentative words	9	9	9	9	9	9
More than six letters	10	10	10	10	10	10
Articles	11	11	11	11	11	11
Prepositions	12	12	12	12	12	12
Anger words	13	13	13	13	13	13
Swear words	14	14	14	14	14	14
Cognitive processes	15	15	15	15	15	15
Words per Sentence	16	16	16	16	16	16
Total Word Count	17	17	17	17	17	17
Flesh-Kincaid Grade Level	18	18	18	18	18	18

2.2 POS Analysis

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

Word Type	Women		Men		Effect Size	
	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Nouns	22.17	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

Word Type	All Women Shortlists		Open Shortlists		Effect Size	
	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 **spaCy** (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 $d \geq |0.2|$ when comparing female Labour MPs by selection process.

2.3 Tokenising / Keyness

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

2.3.1 Men vs Women

Keyness – a linguistic measure of the frequency of different words in two groups of texts – reveals clear gender differences in the most disproportionately common words used by female and male Labour MPs. Unsurprisingly, despite male MPs saying almost twice as many words (30,596,921 vs 15,897,929) 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.

Keyness between Labour MPs, by Gender

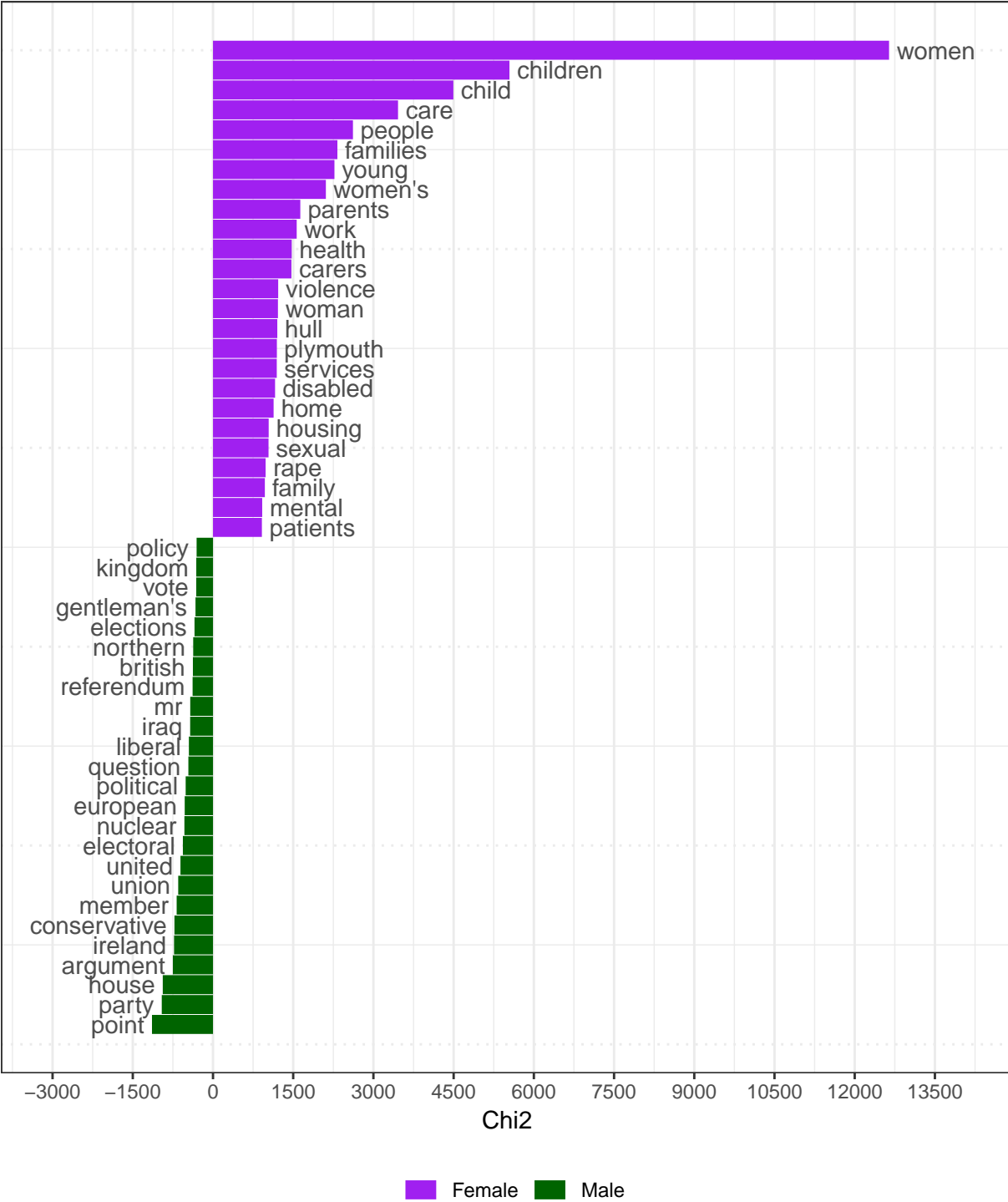


Figure 2: Keyness between Labour MPs, by Gender

2.3.2 Shortlists vs Non-Shortlists

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

Also of note is AWS MPs making more references to their “constituency” and its “constituents”, suggesting that AWS MPs may draw on the fact they were elected by their constituents as a source political legitimacy, at least more than non-AWS MPs.

Keyness between Female Labour MPs, by Selection Process

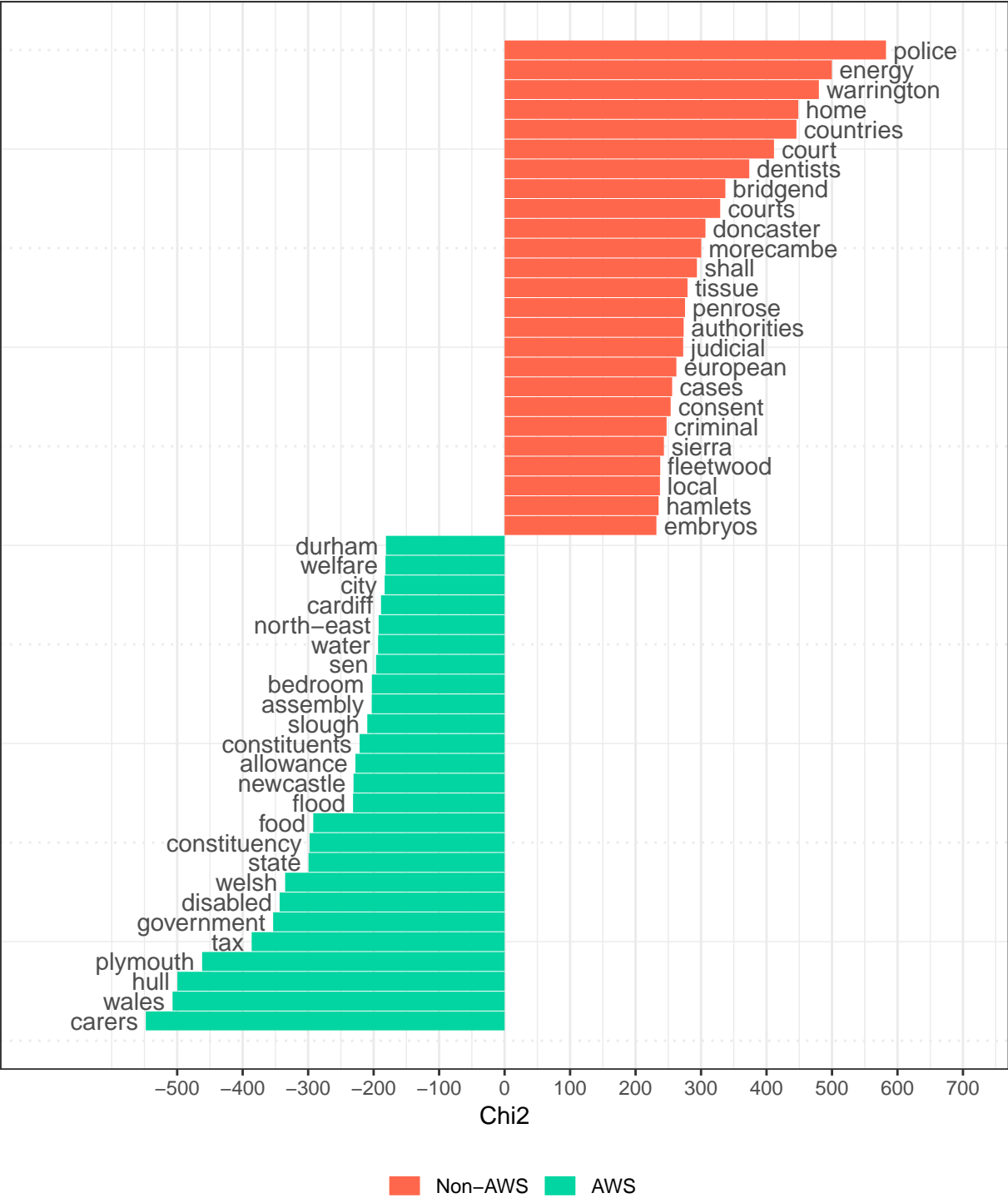


Figure 3: Keyness between Female Labour MPs, by Selection Process

2.3.3 Labour vs Conservative

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

Keyness between Labour and Conservative MPs

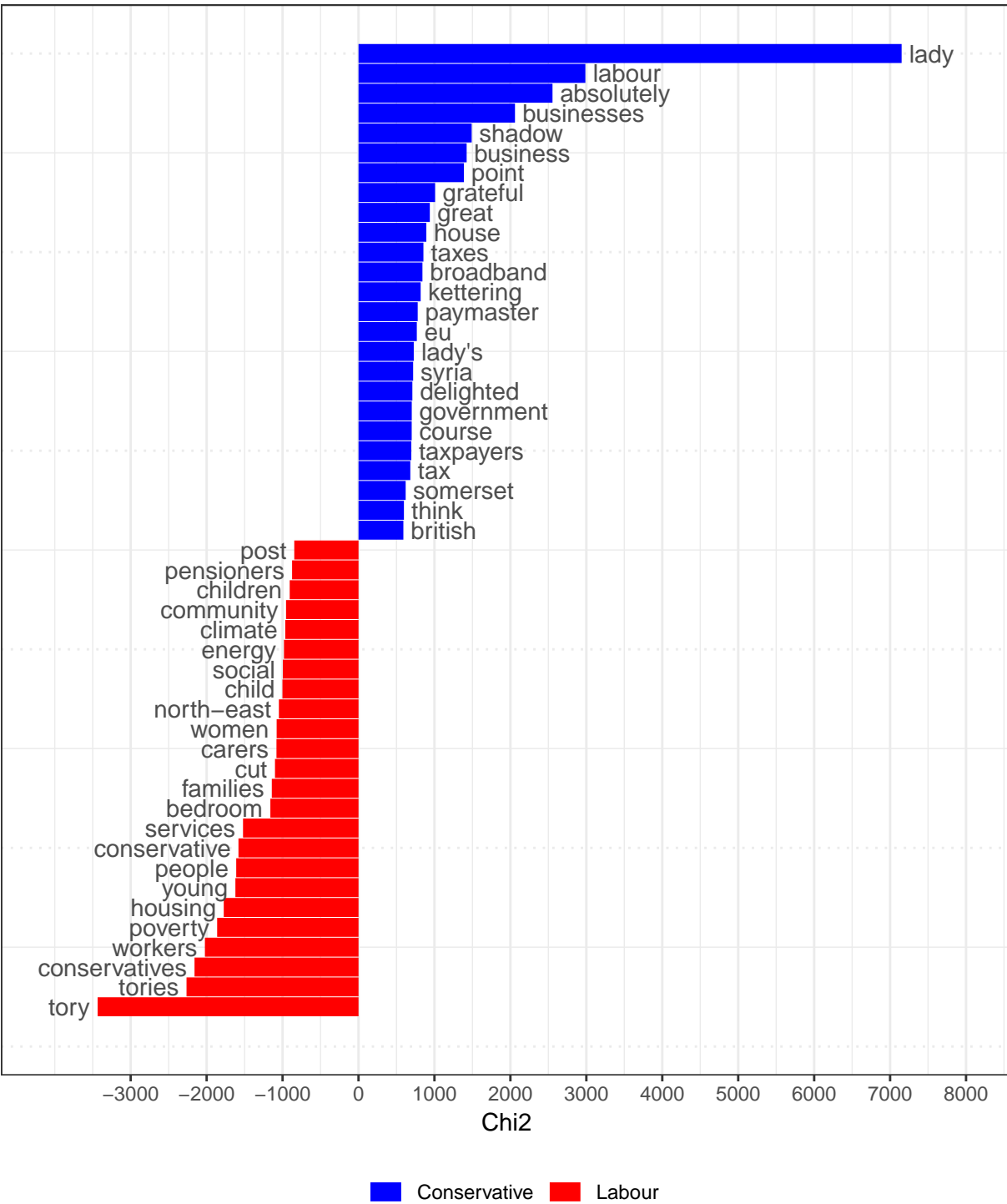


Figure 4: Keyness between Labour and Conservative MPs

2.4 Bigrams

We created bigrams of all first person plural and singular pronouns for female Labour MPs. As above, AWS MPs are far more likely to make references to their constituency or their constituents.

Bigram Keyness in Female Labour MPs by Selection Process

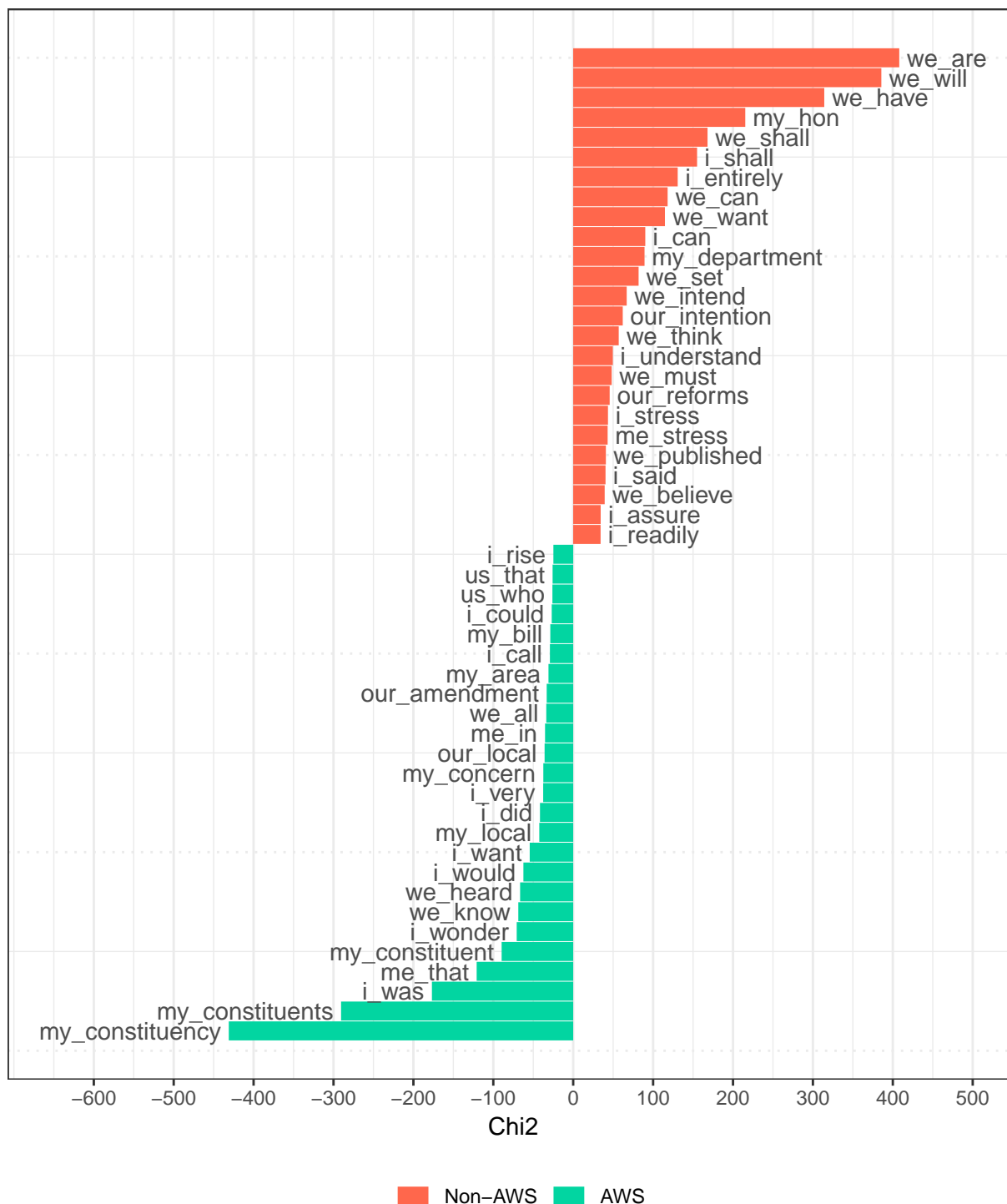


Figure 5: Bigram Keyness in Female Labour MPs by Selection Process

2.5 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.

2.6 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 unsupervised topic models when applied to new sets of texts.

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 data about the writer or speaker into the topic classification algorithm. 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, i.e. the proportion of speeches classified as belonging to each topic can vary as a function of the AWS variable.

We incorporated the AWS status of speakers into our topic model, using all speeches by female Labour MPs, with their AWS status as a covariate in classifying topics. We then matched these topics to speeches by male Labour MPs.

In addition to the structured topic model presented below, we produced three additional STM implementations, with different numbers of topics (K),

The first implementation used an algorithm developed by Lee & Mimno (2014), implemented in the `stm` package (Roberts et al., 2018), to estimate the number of topics across all speeches made by female Labour MPs, using the “spectral” method developed by Arora et al. (2013), implemented by Roberts et al. (2018). The resulting topic model has 84 topics, across 81,651 documents and a dictionary of 119,586 words. However, the topic quality with $K = 84$ is poor, and several topics have poor semantic coherence (see Figure 21, and the appendix), or contain only one or two speeches.

2.6.1 Shortlists vs Non-Shortlists - K45

As seen in the word lists in the appendix, there is relatively scattershot semantic coherence, although exclusivity is high, when using the 84 topic models suggested by Lee and Mimno’s (2014) algorithm. We therefore re-ran the analysis, using 45 topic models, which resulted in increased semantic coherence, albeit with slightly lower exclusivity, as illustrated in Figure 7. The lower number of models also makes hand-coding of the content of topics more straightforward. The $K = 45$ topic model has 81,651 documents and uses a dictionary of 119,586 words, like the $K = 84$ model. Models with $K = 30$ and $K = 60$ were also produced and are available in the appendix.

We created a Fruchterman-Reingold (Fruchterman & Reingold, 1991) diagram to show the connections between different topics. Larger vertices indicate more common topics, and the plot uses a colour scale to indicate the proportion of speeches classed in that topic made by AWS and non-AWS female Labour MPs. The space between vertices indicate the closeness or distance of two topics. E.g. closer vertices represent topics with more overlapping words than more distant topics.

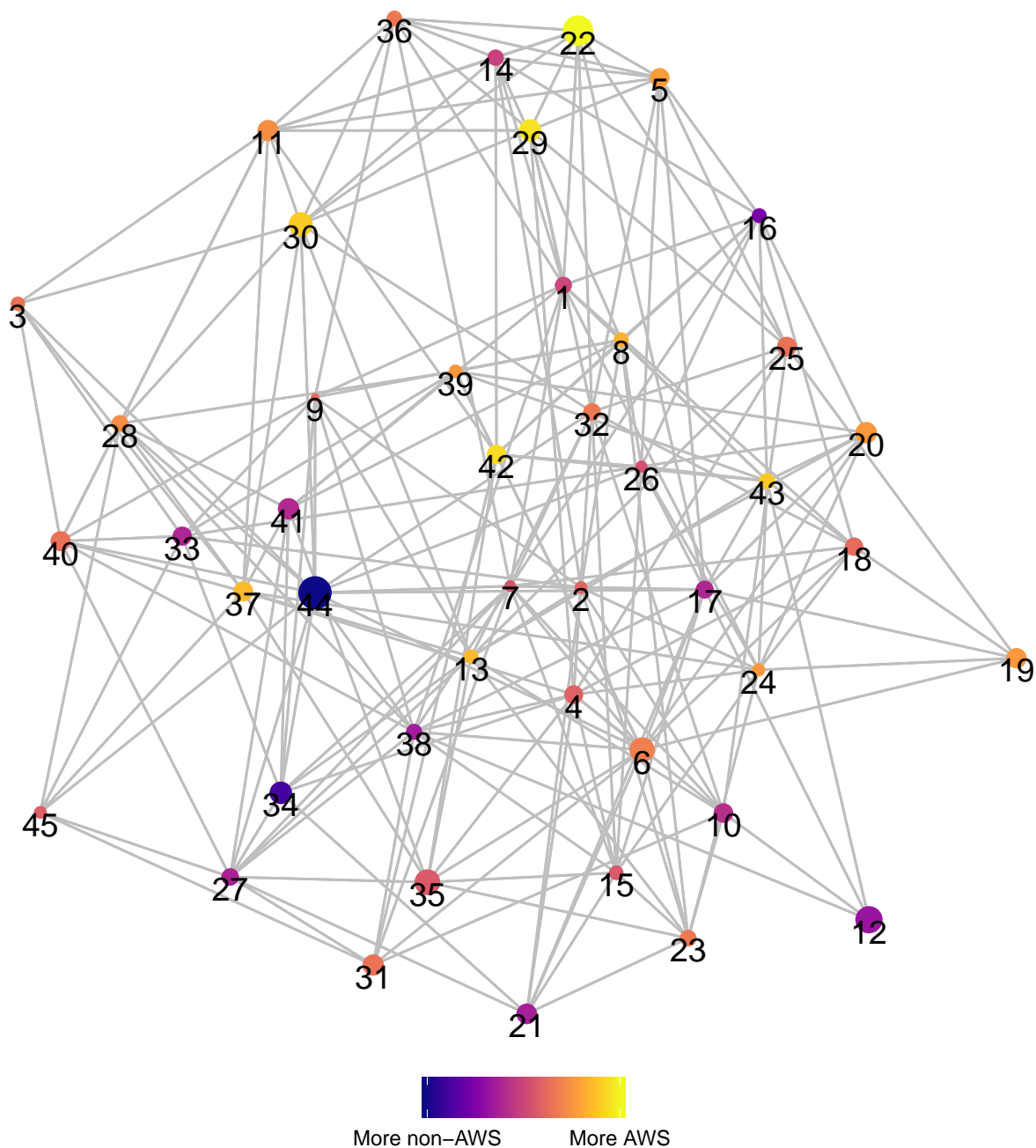


Figure 6: Fruchterman-Reingold plot of k45 Network

The `stm` package includes the `estimateEffect` function to create a regression model (Table ??) using individual documents (speeches) as individual observations, with the number of documents fitting each topic as the dependent variable and model covariates (AWS status) as independent variables.

Table 9: Estimate Effects – k45

	Estimate	Standard Error	t value	Pr(> t)	
Topic 1 – Business					
Intercept	0.0204958	0.0004329	47.3467876	< 0.001	***
Shortlist	-0.0027691	0.0005666	-4.8872095	< 0.001	***
Topic 2 – Roads					
Intercept	0.0111615	0.0003749	29.7716978	< 0.001	***
Shortlist	0.0000016	0.0004469	0.0035142	> 0.99	
Topic 3 – Members					
Intercept	0.0181536	0.0003804	47.7192504	< 0.001	***
Shortlist	0.0010556	0.0004723	2.2352260	0.025	*
Topic 4 – Gender					
Intercept	0.0188188	0.0005128	36.7014150	< 0.001	***
Shortlist	-0.0002307	0.0006477	-0.3561886	0.72	
Topic 5 – Housing					
Intercept	0.0155125	0.0005277	29.3945544	< 0.001	***
Shortlist	0.0041747	0.0006687	6.2429969	< 0.001	***
Topic 6 – Questions					
Intercept	0.0369146	0.0003580	103.1188899	< 0.001	***
Shortlist	0.0019953	0.0004524	4.4102219	< 0.001	***
Topic 7 – Technology					
Intercept	0.0193268	0.0002837	68.1288591	< 0.001	***
Shortlist	-0.0015272	0.0003415	-4.4724425	< 0.001	***
Topic 8 – Food and farming					
Intercept	0.0088801	0.0003916	22.6768864	< 0.001	***
Shortlist	0.0056236	0.0005602	10.0380434	< 0.001	***
Topic 9 – Animals					
Intercept	0.0098231	0.0003677	26.7164245	< 0.001	***
Shortlist	0.0004854	0.0004522	1.0733722	0.28	
Topic 10 – Disease					
Intercept	0.0216346	0.0005605	38.5963623	< 0.001	***
Shortlist	-0.0047404	0.0006924	-6.8461277	< 0.001	***
Topic 11 – Parties					
Intercept	0.0315892	0.0004337	72.8378172	< 0.001	***
Shortlist	0.0032155	0.0005346	6.0142936	< 0.001	***
Topic 12 – Health Care					
Intercept	0.0346213	0.0007020	49.3199395	< 0.001	***
Shortlist	-0.0071998	0.0009132	-7.8841790	< 0.001	***
Topic 13 – Disasters					
Intercept	0.0116912	0.0003682	31.7548845	< 0.001	***
Shortlist	0.0062322	0.0005042	12.3613771	< 0.001	***
Topic 14 – Energy					
Intercept	0.0170283	0.0004549	37.4301098	< 0.001	***
Shortlist	-0.0032570	0.0006101	-5.3386605	< 0.001	***
Topic 15 – Volunteering					
Intercept	0.0166924	0.0003704	45.0701025	< 0.001	***
Shortlist	-0.0011789	0.0004441	-2.6547221	0.008	**
Topic 16 – Infrastructure					

Table 9: Estimate Effects – k45 (*continued*)

	Estimate	Standard Error	t value	Pr(> t)	
Intercept	0.0254956	0.0004351	58.6022413	< 0.001	***
Shortlist	-0.0093006	0.0005127	-18.1418165	< 0.001	***
Topic 17 – Local authorities					
Intercept	0.0259259	0.0004091	63.3699770	< 0.001	***
Shortlist	-0.0055094	0.0005033	-10.9468730	< 0.001	***
Topic 18 – Universities and Skills					
Intercept	0.0177181	0.0004548	38.9556066	< 0.001	***
Shortlist	0.0004209	0.0005436	0.7742279	0.44	
Topic 19 – Schools					
Intercept	0.0165371	0.0005400	30.6240404	< 0.001	***
Shortlist	0.0039392	0.0006595	5.9734396	< 0.001	***
Topic 20 – Transport					
Intercept	0.0181343	0.0005811	31.2083836	< 0.001	***
Shortlist	0.0038809	0.0006838	5.6750528	< 0.001	***
Topic 21 – Police					
Intercept	0.0240660	0.0006093	39.4960942	< 0.001	***
Shortlist	-0.0062050	0.0007251	-8.5574945	< 0.001	***
Topic 22 – Budgets and tax					
Intercept	0.0362028	0.0006518	55.5462467	< 0.001	***
Shortlist	0.0099903	0.0008388	11.9104718	< 0.001	***
Topic 23 – Drugs					
Intercept	0.0131285	0.0005701	23.0267303	< 0.001	***
Shortlist	0.0015239	0.0006477	2.3529739	0.019	*
Topic 24 – Culture and sport					
Intercept	0.0082624	0.0003656	22.6018436	< 0.001	***
Shortlist	0.0039145	0.0004534	8.6333403	< 0.001	***
Topic 25 – Children and families					
Intercept	0.0201223	0.0004762	42.2535523	< 0.001	***
Shortlist	0.0008859	0.0005775	1.5340740	0.13	
Topic 26 – Planning and land-use					
Intercept	0.0117411	0.0003697	31.7559494	< 0.001	***
Shortlist	-0.0017143	0.0004543	-3.7734306	< 0.001	***
Topic 27 – Security					
Intercept	0.0213978	0.0004952	43.2138123	< 0.001	***
Shortlist	-0.0059831	0.0005958	-10.0414784	< 0.001	***
Topic 28 – Elections					
Intercept	0.0143882	0.0004492	32.0309385	< 0.001	***
Shortlist	0.0031457	0.0005524	5.6950809	< 0.001	***
Topic 29 – Benefits and pensions					
Intercept	0.0198848	0.0005722	34.7498876	< 0.001	***
Shortlist	0.0087534	0.0007109	12.3127669	< 0.001	***
Topic 30 – Call to action					
Intercept	0.0396842	0.0003958	100.2756886	< 0.001	***
Shortlist	0.0072121	0.0004893	14.7390561	< 0.001	***
Topic 31 – Reports					
Intercept	0.0327890	0.0004264	76.8937843	< 0.001	***

Table 9: Estimate Effects – k45 (*continued*)

	Estimate	Standard Error	t value	Pr(> t)	
Shortlist	0.0010319	0.0005372	1.9209545	0.055	
Topic 32 – Disability					
Intercept	0.0267120	0.0003256	82.0434572	< 0.001	***
Shortlist	0.0015726	0.0004062	3.8715029	< 0.001	***
Topic 33 – Amendments					
Intercept	0.0272216	0.0005576	48.8204471	< 0.001	***
Shortlist	-0.0056708	0.0006424	-8.8270758	< 0.001	***
Topic 34 – Justice					
Intercept	0.0323315	0.0005769	56.0447541	< 0.001	***
Shortlist	-0.0127437	0.0007036	-18.1125783	< 0.001	***
Topic 35 – Military intervention					
Intercept	0.0283417	0.0006953	40.7628170	< 0.001	***
Shortlist	-0.0010530	0.0008639	-1.2188804	0.22	
Topic 36 – Financial system					
Intercept	0.0157149	0.0003763	41.7569964	< 0.001	***
Shortlist	0.0015123	0.0004875	3.1023631	0.002	**
Topic 37 – Debate					
Intercept	0.0236949	0.0003753	63.1356611	< 0.001	***
Shortlist	0.0061842	0.0004965	12.4555200	< 0.001	***
Topic 38 – Public bodies					
Intercept	0.0280934	0.0003804	73.8600364	< 0.001	***
Shortlist	-0.0065559	0.0005163	-12.6968645	< 0.001	***
Topic 39 – Devolution					
Intercept	0.0109082	0.0003858	28.2743818	< 0.001	***
Shortlist	0.0038214	0.0004946	7.7262562	< 0.001	***
Topic 40 – Bills					
Intercept	0.0285229	0.0004088	69.7792326	< 0.001	***
Shortlist	0.0009326	0.0004705	1.9819962	0.047	*
Topic 41 – European Union					
Intercept	0.0259835	0.0005507	47.1828388	< 0.001	***
Shortlist	-0.0052614	0.0006661	-7.8988176	< 0.001	***
Topic 42 – Environment					
Intercept	0.0168770	0.0004281	39.4186789	< 0.001	***
Shortlist	0.0083499	0.0005794	14.4112265	< 0.001	***
Topic 43 – Constituency					
Intercept	0.0132746	0.0004004	33.1560062	< 0.001	***
Shortlist	0.0070774	0.0005358	13.2093296	< 0.001	***
Topic 44 – Responses					
Intercept	0.0676800	0.0004190	161.5393323	< 0.001	***
Shortlist	-0.0154071	0.0005217	-29.5307288	< 0.001	***
Topic 45 – Interventions					
Intercept	0.0168112	0.0003053	55.0720974	< 0.001	***
Shortlist	-0.0005789	0.0003821	-1.5148779	0.13	

In all but 8 topics (Roads, Gender, Animals, Universities and Skills, Children and families, Reports, Military intervention, Interventions) the model found p values of < 0.05 , and in every topic except the aforementioned

and Members, Volunteering, Drugs, Financial system, Bills, p values of < 0.001 .

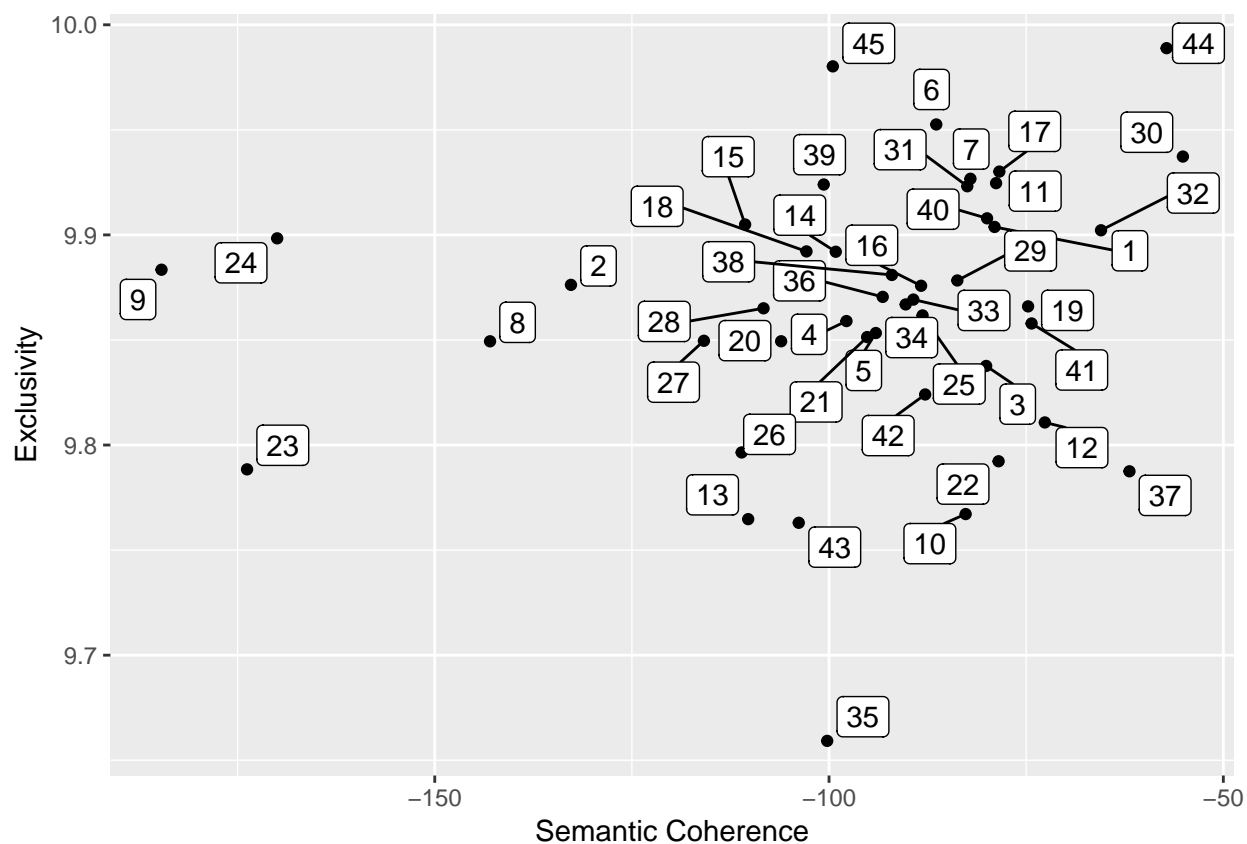


Figure 7: Coherence of k45 Topic Models

Table 10: Distribution of Topics Among Female Labour MPs – K45

Topic	One or more speeches	Five or more speeches
1 – Business	140	72
10 – Disease	143	74
11 – Parties	152	96
12 – Health Care	155	114
13 – Disasters	150	79
14 – Energy	128	57
15 – Volunteering	132	64
16 – Infrastructure	132	57
17 – Local authorities	141	72
18 – Universities and Skills	149	87
19 – Schools	139	96
2 – Roads	128	55
20 – Transport	149	89
21 – Police	147	81
22 – Budgets and tax	157	127
23 – Drugs	125	66
24 – Culture and sport	131	66

Table 10: Distribution of Topics Among Female Labour MPs – K45
(continued)

Topic	One or more speeches	Five or more speeches
25 – Children and families	143	82
26 – Planning and land-use	113	45
27 – Security	127	61
28 – Elections	135	70
29 – Benefits and pensions	151	93
3 – Members	129	67
30 – Call to action	156	116
31 – Reports	155	101
32 – Disability	144	86
33 – Amendments	123	57
34 – Justice	146	82
35 – Military intervention	155	112
36 – Financial system	124	56
37 – Debate	161	105
38 – Public bodies	119	52
39 – Devolution	104	43
4 – Gender	149	85
40 – Bills	136	79
41 – European Union	152	91
42 – Environment	143	89
43 – Constituency	151	81
44 – Responses	158	123
45 – Interventions	120	40
5 – Housing	141	74
6 – Questions	165	132
7 – Technology	121	49
8 – Food and farming	123	57
9 – Animals	109	32

Table 11: Count and Distribution of Topics – k45

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
Topic 1	759	1.41%	576	2.07%	2,841	1.68%
Topic 2	552	1.03%	297	1.07%	1,908	1.13%
Topic 3	667	1.24%	323	1.16%	2,646	1.56%
Topic 4	1,092	2.03%	568	2.04%	587	0.35%
Topic 5	1,299	2.42%	478	1.72%	2,048	1.21%
Topic 6	2,286	4.25%	857	3.08%	4,633	2.74%
Topic 7	508	0.94%	255	0.92%	1,046	0.62%
Topic 8	825	1.53%	245	0.88%	2,338	1.38%
Topic 9	450	0.84%	207	0.74%	1,192	0.7%
Topic 10	994	1.85%	788	2.83%	1,565	0.92%
Topic 11	1,491	2.77%	663	2.38%	7,505	4.43%

Table 11: Count and Distribution of Topics – k45 (*continued*)

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
Topic 12	2,255	4.19%	1,577	5.66%	4,855	2.87%
Topic 13	795	1.48%	222	0.8%	1,663	0.98%
Topic 14	673	1.25%	569	2.04%	2,183	1.29%
Topic 15	668	1.24%	351	1.26%	1,279	0.76%
Topic 16	477	0.89%	569	2.04%	2,165	1.28%
Topic 17	855	1.59%	649	2.33%	3,107	1.83%
Topic 18	1,058	1.97%	512	1.84%	3,239	1.91%
Topic 19	1,430	2.66%	529	1.9%	3,491	2.06%
Topic 20	1,601	2.98%	582	2.09%	4,181	2.47%
Topic 21	1,199	2.23%	815	2.93%	3,112	1.84%
Topic 22	3,712	6.9%	1,295	4.65%	10,692	6.31%
Topic 23	903	1.68%	386	1.39%	1,762	1.04%
Topic 24	647	1.2%	219	0.79%	1,773	1.05%
Topic 25	1,179	2.19%	619	2.22%	1,275	0.75%
Topic 26	486	0.9%	291	1.04%	1,363	0.8%
Topic 27	766	1.42%	652	2.34%	2,041	1.21%
Topic 28	1,006	1.87%	328	1.18%	4,391	2.59%
Topic 29	1,818	3.38%	594	2.13%	3,335	1.97%
Topic 30	2,247	4.18%	621	2.23%	8,740	5.16%
Topic 31	1,482	2.76%	683	2.45%	4,975	2.94%
Topic 32	992	1.84%	429	1.54%	1,624	0.96%
Topic 33	971	1.81%	742	2.66%	4,525	2.67%
Topic 34	1,215	2.26%	1,239	4.45%	4,451	2.63%
Topic 35	2,153	4%	1,223	4.39%	9,983	5.9%
Topic 36	755	1.4%	360	1.29%	2,030	1.2%
Topic 37	1,409	2.62%	460	1.65%	5,138	3.03%
Topic 38	676	1.26%	508	1.82%	2,387	1.41%
Topic 39	716	1.33%	203	0.73%	2,374	1.4%
Topic 40	1,344	2.5%	539	1.93%	5,389	3.18%
Topic 41	1,271	2.36%	918	3.29%	5,573	3.29%
Topic 42	1,380	2.57%	394	1.41%	3,854	2.28%
Topic 43	896	1.67%	277	0.99%	1,823	1.08%
Topic 44	3,309	6.15%	2,931	10.52%	19,842	11.72%
Topic 45	521	0.97%	320	1.15%	2,417	1.43%



Figure 8: k45 Pyramid Chart

Figure 8 is a pyramid plot, showing the percentage of speeches classed in each topic of AWS and non-AWS MPs.

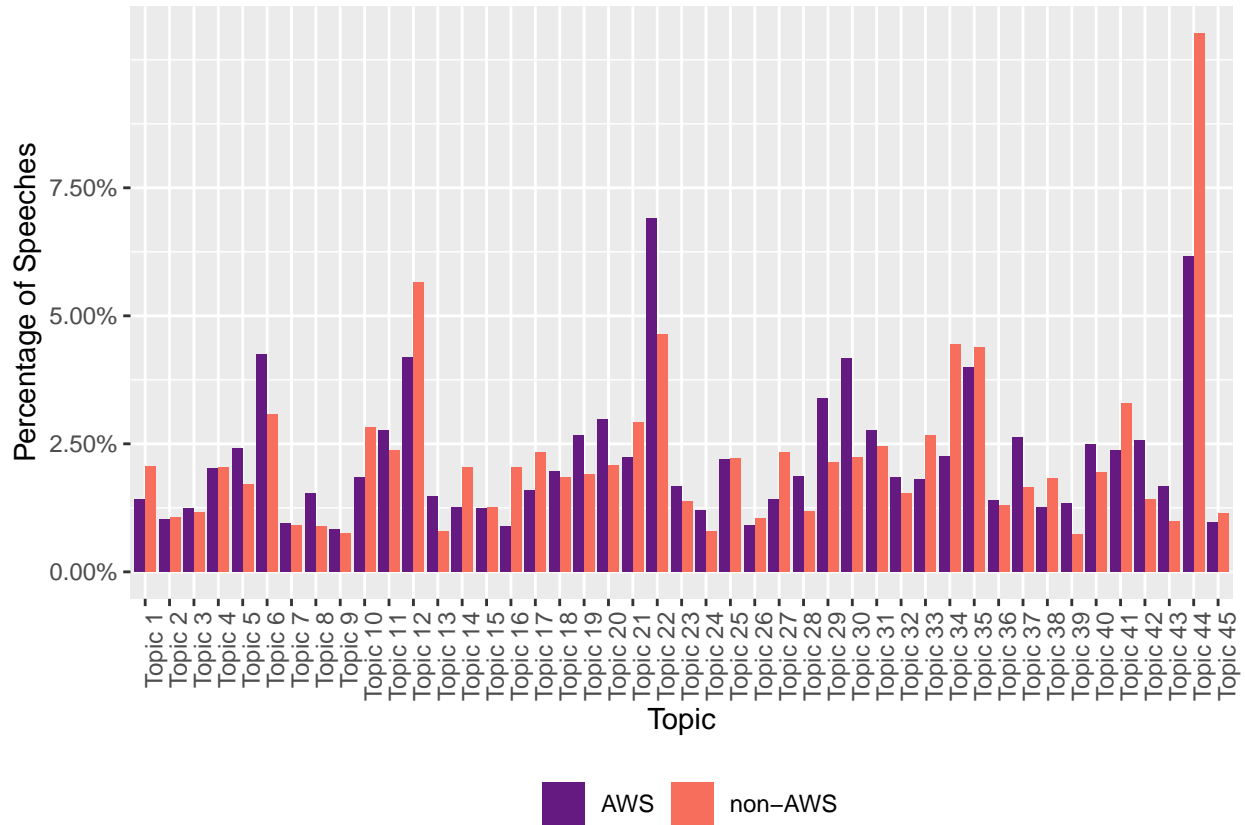


Figure 9: k45 Bar Chart

2.6.1.1 Word Occurences

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).

Table 12: Words in topic - k45

Topic Number	Top Ten Words	Top Ten FREX
Topic 1	business, businesses, companies, small, tax, company, sector, economy, industry, private, uk, employees, public, economic, enterprise, finance, rates, contracts, revenue, firms	businesses, medium-sized, avoidance, employees, enterprise, corporation, business, hmrc, enterprises, smes, shares, employee, firms, competitiveness, stamp, revenue, company, small, evasion, entrepreneurs
Topic 2	safety, road, bbc, air, licence, car, vehicles, traffic, driving, vehicle, cars, drivers, roads, use, radio, public, noise, also, health, number	caa, herbal, vehicles, primodos, accidents, taxi, bbc, drivers, pedestrians, parking, fireworks, noise, radio, cycling, nats, licence, vehicle, hse, bikes, mph

Table 12: Words in topic - k45 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 3	member, members, debate, said, made, also, north, heard, spoke, south, friends, raised, east, mentioned, talked, speech, west, comments, pointed, issues	member, thoughtful, spoke, eastmr, westmr, hayes, eloquently, southmr, northmr, bermondsey, dorsetmr, bromley, holborn, durhammr, talked, wright, redwood, selly, rushcliffemr, greenmr
Topic 4	women, violence, men, domestic, equality, women's, pay, discrimination, equal, woman, rights, sexual, girls, gender, work, victims, marriage, many, trafficking, sex	gender, women, women's, fgm, discrimination, equality, female, men, male, equalities, equal, slavery, marriage, gay, violence, trafficked, girls, marriages, transgender, domestic
Topic 5	housing, homes, private, social, home, affordable, london, accommodation, sector, rent, need, property, properties, tenants, landlords, buy, council, rented, many, bedroom	rent, tenants, landlords, rented, homelessness, homeless, rents, tenancies, tenancy, leasehold, properties, housing, landlord, accommodation, leaseholders, affordable, two-bedroom, homes, renting, bedroom
Topic 6	agree, ensure, made, support, make, aware, welcome, department, progress, thank, taking, work, recent, government, statement, can, action, given, assessment, continue	agree, aware, progress, steps, thank, friend's, assessment, recent, taking, department, assure, ensure, statement, welcome, discussions, strategy, reply, plans, discuss, commitment
Topic 7	information, service, access, advice, available, services, staff, provide, data, use, can, agency, provided, guidance, also, providers, ensure, national, agencies, system	information, data, advice, pilot, broadband, digital, communication, access, pilots, records, electronic, advisers, providers, telephone, computer, service, check, communications, hearing, communicate
Topic 8	food, plymouth, farmers, industry, environment, waste, rural, marine, sea, fishing, cornwall, products, environmental, fish, uk, meat, agricultural, fisheries, farming, affairs	marine, fishing, fisheries, fishermen, cod, beef, gm, dairy, camborne, plymouth, fish, seafarers, meat, mmo, cornwall, farmers, food, agriculture, sugar, cornish
Topic 9	regulation, insurance, regulatory, animals, code, industry, fsa, dogs, dog, animal, ombudsman, welfare, standards, ban, regime, protection, enforcement, act, lord, regulator	dogs, dog, policyholders, fur, mink, sia, mesothelioma, circuses, fsa, snares, rspca, penrose, ombudsman, maladministration, regulatory, animals, animal, regulation, wild, regulators
Topic 10	health, treatment, cancer, mental, research, medical, disease, condition, patients, can, national, also, conditions, screening, risk, group, one, many, heart, diagnosis	embryos, prostate, cervical, hepatitis, cancers, transplant, fertilisation, embryonic, endometriosis, cancer, piercing, immunisation, flu, diabetes, anaemia, cord, cells, abortion, screening, embryology

Table 12: Words in topic - k45 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 11	government, labour, conservative, policy, opposition, party, government's, said, members, previous, us, say, now, ministers, back, public, let, liberal, conservatives, nothing	conservative, conservatives, liberal, tory, tories, democrats, labour, manifesto, benches, opposition, democrat, coalition, promises, interruption, promise, lib, party, party's, government, previous
Topic 12	health, care, nhs, services, hospital, patients, service, staff, social, trust, hospitals, trusts, patient, doctors, primary, new, nurses, waiting, need, emergency	dentists, dentistry, helier, dental, pct, dentist, nurses, hospitals, nhs, hospital, discharges, trusts, commissioning, e, pharmacies, beds, nursing, gp, doctors, dementia
Topic 13	family, constituent, mr, families, man, years, fire, death, case, died, life, told, two, lost, mrs, home, mother, received, lives, day	firefighters, mrs, constituent, fire, died, son, daughter, ms, husband, tragedy, loved, fires, wife, contacted, tragically, funeral, tragic, sister, man, rescue
Topic 14	energy, market, fuel, companies, water, prices, price, bills, consumers, competition, gas, customers, efficiency, oil, consumer, electricity, winter, costs, poverty, households	ofgem, fuel, electricity, gas, supplier, energy, tariff, prices, oil, water, meters, bills, winter, suppliers, price, aluminium, insulation, tariffs, heat, wholesale
Topic 15	community, organisations, groups, voluntary, communities, society, sector, social, prison, charities, support, organisation, role, charity, church, many, faith, can, together, group	volunteering, voluntary, charities, prisons, organisations, church, volunteers, probation, prisoners, charity, religious, prison, charitable, faith, volunteer, groups, reoffending, gift, milton, community
Topic 16	new, investment, areas, post, office, building, rural, programme, communities, future, build, years, development, infrastructure, offices, million, projects, need, country, economic	post, offices, mail, regeneration, investment, rural, urban, vision, invested, building, infrastructure, sub-post, investing, renewal, closures, build, gateway, invest, projects, sub-postmasters
Topic 17	local, authorities, funding, council, authority, areas, government, councils, services, area, money, resources, communities, needs, grant, level, proposals, provision, fund, provide	authorities, local, councils, funding, authority, grant, formula, councillors, allocation, allocated, council, county, unitary, locally, hertfordshire, allocations, grants, resources, settlement, bids
Topic 18	education, skills, training, young, students, university, college, higher, science, employers, opportunities, apprenticeships, universities, colleges, research, learning, engineering, student, qualifications, courses	students, apprenticeships, universities, ema, fe, graduates, colleges, apprenticeship, student, skills, vocational, qualifications, courses, university, careers, engineering, sixth-form, training, apprentices, college

Table 12: Words in topic - k45 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 19	schools, school, education, children, teachers, parents, pupils, educational, special, needs, primary, good, free, standards, learning, teacher, teaching, secondary, provision, autism	schools, teachers, pupils, sen, academies, ofsted, pupil, grammar, school, educational, teacher, autism, leas, academisation, academy, classroom, curriculum, attainment, teaching, dyslexia
Topic 20	transport, london, rail, regional, bus, services, line, travel, train, network, passengers, regions, capacity, manchester, fares, public, region, service, trains, station	rail, bus, passengers, fares, railways, hs2, freight, high-speed, electrification, crossrail, railtrack, trains, transport, passenger, buses, heathrow, fare, railway, commuter, concessionary
Topic 21	police, crime, officers, behaviour, policing, antisocial, community, force, forces, communities, tackle, neighbourhood, powers, home, serious, can, chief, streets, officer, number	policing, antisocial, graffiti, crime, officers, police, constable, pcsos, asbos, behaviour, gang, cctv, neighbourhood, knife, constables, violent, anti-social, gangs, dna, constabulary
Topic 22	million, year, budget, cuts, cut, billion, tax, government, increase, chancellor, jobs, economy, spending, years, pay, last, growth, government's, impact, economic	obr, budget, millionaires, wage, cuts, cut, billion, deficit, vat, recession, spending, unemployment, wages, inflation, chancellor, hit, fiscal, 50p, 2010, chancellor's
Topic 23	alcohol, drugs, people, drug, smoking, young, use, ban, tobacco, israel, advertising, public, online, problem, drinking, health, misuse, palestinian, cannabis, israeli	tobacco, cannabis, cull, tb, palestinians, hamas, pornography, israelis, sunbeds, psychoactive, sunbed, israeli, gaza, culls, alcohol, palestinian, israel's, misuse, israel, smoking
Topic 24	culture, sport, media, football, clubs, arts, club, sports, bradford, slough, games, creative, cultural, tickets, music, many, swimming, lottery, olympic, industry	sport, games, gambling, betting, venues, lap-dancing, touts, football, casinos, sporting, hove, slough, bradford, arts, swimming, sports, olympic, music, creative, musicians
Topic 25	children, child, care, families, parents, family, carers, support, children's, poverty, social, young, working, many, vulnerable, start, parent, home, one, can	csa, same-sex, child, lone, carers, parent, children's, childcare, caring, couples, adoption, children, mothers, child's, parents, carer, adopters, cafcass, fathers, trans
Topic 26	planning, land, development, sites, site, national, green, buildings, use, policy, new, building, environment, plan, co-operative, application, applications, area, permission, forest	gypsies, gypsy, planning, brownfield, land, sites, co-operative, belt, site, gospels, nppf, forestry, spaces, developers, hectares, forest, forests, restoration, travellers, gardens
Topic 27	home, secretary, security, inquiry, investigation, office, terrorism, serious, threat, powers, control, police, orders, fraud, need, evidence, prevent, intelligence, also, risk	tpims, isc, sfo, reviewer, terrorism, investigations, tpim, intercept, investigation, detention, terrorist, proscription, intelligence, inquiry, ipcc, fraud, secretary's, counter-terrorism, hillsborough, suspects

Table 12: Words in topic - k45 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 28	vote, political, parliament, people, election, parties, elected, party, elections, democracy, register, electoral, one, voting, referendum, registration, politics, members, system, democratic	electoral, polling, voting, vote, turnout, votes, referendums, voter, elections, voters, political, gibraltar, parliaments, elected, ballot, electorate, democracy, constitution, canvass, candidates
Topic 29	benefit, tax, pension, benefits, credit, income, pensions, pensioners, allowance, system, changes, scheme, state, pay, age, universal, savings, welfare, government, paid	pension, claimants, pensions, pensioners, allowance, retirement, pensioner, income, uprating, earnings, credits, universal, cpi, esa, entitlement, benefits, benefit, carer's, jobseeker's, dwp
Topic 30	one, get, time, going, go, just, know, say, think, said, even, things, problem, like, back, many, now, us, another, want	going, things, get, lot, something, really, go, thing, talking, got, saying, enough, told, else, bit, happen, happening, think, anything, thought
Topic 31	report, review, year, last, said, response, decision, published, number, asked, questions, consultation, evidence, since, received, ministers, made, may, following, office	report, official, published, review, vol, march, july, january, written, response, november, december, october, june, february, publish, questions, september, april, letter
Topic 32	people, work, young, many, help, support, need, get, disabled, can, employment, constituency, job, working, lives, people's, want, life, disability, often	disabled, people, disability, people's, work, disabilities, job, youth, unemployed, older, employment, young, pip, help, getting, jobcentre, lives, get, dla, elderly
Topic 33	clause, amendment, new, amendments, act, provisions, regulations, section, 1, power, provision, clauses, made, apply, may, 2, powers, tabled, person, make	nos, clause, clauses, amendments, insert, amendment, affirmative, schedule, section, provisions, page, definition, regulations, tabled, b, amend, wording, drafted, amended, specified
Topic 34	cases, law, court, legal, justice, case, criminal, courts, offence, rights, evidence, system, victims, act, offences, person, appeal, human, protection, prosecution	defendants, defendant, court, courts, magistrates, prosecution, offence, judges, cps, conviction, tribunal, judge, witnesses, convictions, offences, jury, lawyers, criminal, judiciary, crb
Topic 35	international, defence, world, forces, countries, armed, war, foreign, human, development, aid, rights, government, un, conflict, military, security, british, united, country	military, iraq, humanitarian, veterans, nato, sri, sierra, zimbabwe, burma, iraqi, leone, kashmir, yemen, daesh, afghan, ceasefire, congo, burmese, assad, taliban
Topic 36	financial, money, bank, debt, scheme, banks, credit, costs, pay, cost, interest, payments, fees, paid, fund, unions, banking, loan, payment, loans	loan, lending, payday, fca, lenders, debt, bank, banking, banks, farepak, debts, loans, financial, rock, bonuses, mortgage, rbs, bankers, taxpayer, creditors
Topic 37	debate, members, many, today, us, speech, house, day, time, first, great, speak, years, leader, opportunity, thank, like, country, proud, parliament	backbench, leader, proud, speak, queen's, speech, privilege, back-bench, anniversary, gracious, fought, speaking, honour, holocaust, chamber, tomorrow, apologise, mp, pride, celebrate

Table 12: Words in topic - k45 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 38	public, commission, role, work, new, independent, standards, set, framework, national, paper, board, bodies, ensure, arrangements, also, practice, white, civil, duty	audit, framework, bodies, commission, accountability, responsibilities, governance, board, independent, white, functions, appointments, paper, accountable, duties, civil, objectives, arrangements, servants, body
Topic 39	wales, scotland, scottish, northern, england, ireland, welsh, assembly, devolution, united, parliament, uk, kingdom, devolved, cardiff, government, powers, english, national, executive	wales, scotland, scottish, ireland, welsh, snp, scotland's, holyrood, cymru, calman, assembly, scots, nationalists, s4c, devolved, devolution, newport, cardiff, northern, administrations
Topic 40	bill, committee, members, legislation, debate, time, hope, proposals, select, support, many, opportunity, scrutiny, concerns, place, detail, believe, changes, measures, reading	committee, bill, select, scrutiny, detail, legislation, debated, bill's, reading, discussion, draft, committees, passage, debates, committee's, consensus, discussed, principle, legislative, scrutinise
Topic 41	european, uk, eu, union, countries, trade, europe, british, country, states, immigration, united, britain, us, rights, foreign, negotiations, asylum, workers, treaty	asylum, nationals, enlargement, treaty, lisbon, immigration, dubs, seekers, european, brexit, eu, europe, accession, eurozone, migration, negotiations, passport, union, migrants, france
Topic 42	secretary, state, change, climate, industry, green, jobs, future, government, can, uk, risk, flood, steel, state's, power, carbon, need, new, wind	solar, flood, steel, state's, climate, renewables, state, low-carbon, flooding, wind, secretary, floods, energy-intensive, carbon, tata, defences, nuclear, renewable, nissan, decarbonisation
Topic 43	constituency, city, centre, constituents, area, town, west, north, hull, council, south, residents, petition, yorkshire, east, local, many, jobs, north-east, one	petitioners, visteon, swindon, humber, hull, petition, burton, yorkshire, halifax, hull's, declares, newcastle, warrington, hackney, town, wakefield, tyneside, lincolnshire, immingham, valley
Topic 44	can, important, point, take, need, issue, make, want, issues, whether, must, however, understand, look, sure, different, hope, well, know, consider	point, important, understand, issue, look, different, certainly, makes, consider, issues, matter, take, possible, extremely, making, sure, whether, want, decisions, course
Topic 45	house, question, order, move, mr, speaker, put, motion, lords, deputy, agreed, time, read, lord, second, ask, beg, minutes, commons, shall	question, lords, beg, motion, speaker, house, agrees, forthwith, order, noble, deputy, agreed, indicated, read, o'clock, notes, madam, move, mr, minutes

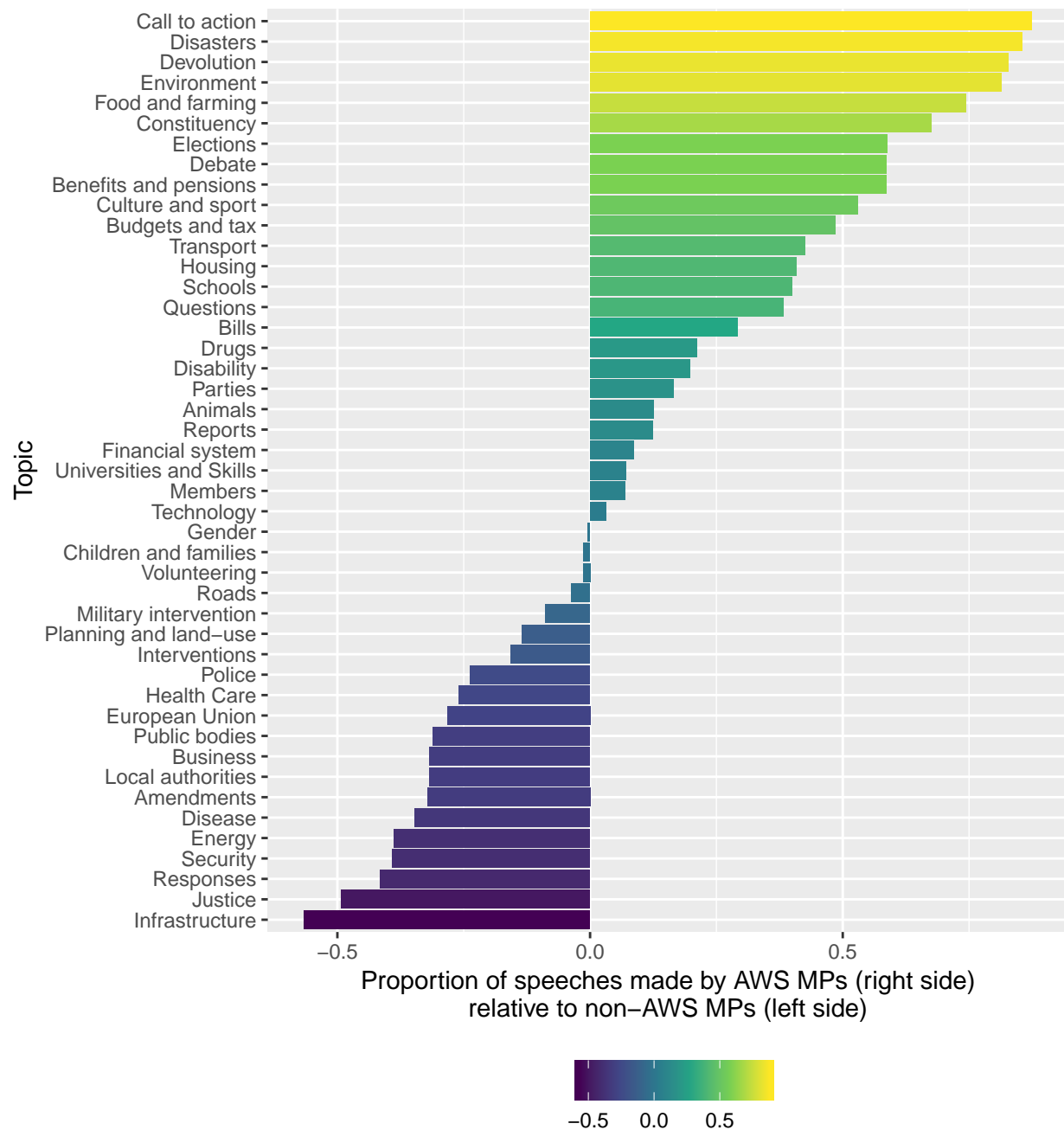


Figure 10: k45 Topic Proportions

2.6.2 Full topic model summary - k45

A topic model with 45 topics, 81651 documents and a 119586 word dictionary.

Topic 1 Top Words:

Highest Prob: business, businesses, companies, small, tax, company, sector

FREX: businesses, medium-sized, avoidance, employees, enterprise, corporation, business

Lift: 1,643, 3.12, 32.2, aaronson, anti-abuse, anti-tax, bacs

Score: businesses, tax, companies, business, company, avoidance, hmrc

Topic 2 Top Words:

Highest Prob: safety, road, bbc, air, licence, car, vehicles
 ## FREX: caa, herbal, vehicles, primodos, accidents, taxi, bbc
 ## Lift: aerodromes, blagdon, bonfires, caa, csm, gatwick's, grantee
 ## Score: bbc, safety, vehicles, traffic, licence, road, fireworks
 ## Topic 3 Top Words:
 ## Highest Prob: member, members, debate, said, made, also, north
 ## FREX: member, thoughtful, spoke, eastmr, westmr, hayes, eloquently
 ## Lift: acoba, erdington, islesmr, northsteve, sedgemore, shoreditchmr, strathspey
 ## Score: member, north, members, spoke, east, south, debate
 ## Topic 4 Top Words:
 ## Highest Prob: women, violence, men, domestic, equality, women's, pay
 ## FREX: gender, women, women's, fgm, discrimination, equality, female
 ## Lift: 77p, amirah, berelowitz, bishoprics, board-level, bride, brothel-keeping
 ## Score: women, violence, women's, men, equality, sexual, discrimination
 ## Topic 5 Top Words:
 ## Highest Prob: housing, homes, private, social, home, affordable, london
 ## FREX: rent, tenants, landlords, rented, homelessness, homeless, rents
 ## Lift: 1,624, afon, bramwell, bron, clearsprings, commonhold, infestation
 ## Score: housing, homes, rent, tenants, rented, landlords, affordable
 ## Topic 6 Top Words:
 ## Highest Prob: agree, ensure, made, support, make, aware, welcome
 ## FREX: agree, aware, progress, steps, thank, friend's, assessment
 ## Lift: ina, manya, ona, 10.42, 101269, 101548, 101549
 ## Score: statement, agree, department, assessment, aware, steps, progress
 ## Topic 7 Top Words:
 ## Highest Prob: information, service, access, advice, available, services, staff
 ## FREX: information, data, advice, pilot, broadband, digital, communication
 ## Lift: north-westdr, saneline, 1,001, 1,752, 1,997, 109648, 114061
 ## Score: information, service, advice, data, access, staff, digital
 ## Topic 8 Top Words:
 ## Highest Prob: food, plymouth, farmers, industry, environment, waste, rural
 ## FREX: marine, fishing, fisheries, fishermen, cod, beef, gm
 ## Lift: fishermen, incineration, inshore, mmo, 0157, 1-tonne, 1,004
 ## Score: food, farmers, plymouth, marine, fishing, fisheries, fishermen
 ## Topic 9 Top Words:
 ## Highest Prob: regulation, insurance, regulatory, animals, code, industry, fsa
 ## FREX: dogs, dog, policyholders, fur, mink, sia, mesothelioma
 ## Lift: 13652, 13653, 13654, arculus, attachment-free, attribution, bee-friendly
 ## Score: fsa, animals, regulation, dogs, regulatory, insurance, animal
 ## Topic 10 Top Words:
 ## Highest Prob: health, treatment, cancer, mental, research, medical, disease
 ## FREX: embryos, prostate, cervical, hepatitis, cancers, transplant, fertilisation
 ## Lift: embryonic, endometriosis, fibrosis, hfea, piercing, @cfaware, #500
 ## Score: cancer, mental, health, patients, disease, treatment, screening
 ## Topic 11 Top Words:
 ## Highest Prob: government, labour, conservative, policy, opposition, party, government's
 ## FREX: conservative, conservatives, liberal, tory, tories, democrats, labour
 ## Lift: lib, #nationalistsconfused, 1.135, 1125, 15-years, 1945-51, 1980s-interruption
 ## Score: conservative, government, labour, party, liberal, opposition, conservatives
 ## Topic 12 Top Words:
 ## Highest Prob: health, care, nhs, services, hospital, patients, service
 ## FREX: dentists, dentistry, helier, dental, pct, dentist, nurses
 ## Lift: #10.89, #14, #20, #225, #3.3, #47, #620
 ## Score: nhs, patients, care, hospital, health, patient, hospitals


```

## Topic 13 Top Words:
## Highest Prob: family, constituent, mr, families, man, years, fire
## FREX: firefighters, mrs, constituent, fire, died, son, daughter
## Lift: firefighters, #ftvote, #timeforthetruth, 03, 0315, 0345, 1,000-year
## Score: constituent, fire, mr, mrs, died, family, ambulance
## Topic 14 Top Words:
## Highest Prob: energy, market, fuel, companies, water, prices, price
## FREX: ofgem, fuel, electricity, gas, supplier, energy, tariff
## Lift: 1,105, 1,345, 106.89, 6,196, 840,000, abebrese, able-to-pay
## Score: energy, fuel, prices, consumers, gas, water, electricity
## Topic 15 Top Words:
## Highest Prob: community, organisations, groups, voluntary, communities, society, sector
## FREX: volunteering, voluntary, charities, prisons, organisations, church, volunteers
## Lift: aid-style, allison's, atheists, bronzefield, caron, cascs, catholicism
## Score: community, prison, organisations, voluntary, charities, prisons, prisoners
## Topic 16 Top Words:
## Highest Prob: new, investment, areas, post, office, building, rural
## FREX: post, offices, mail, regeneration, investment, rural, urban
## Lift: sub-post, #1.8, #21.5, #210, #28.5, #450, 0207
## Score: investment, post, rural, regeneration, offices, mail, infrastructure
## Topic 17 Top Words:
## Highest Prob: local, authorities, funding, council, authority, areas, government
## FREX: authorities, local, councils, funding, authority, grant, formula
## Lift: banham, brs-bids, central-local, devolves, lga's, maas, merrick
## Score: local, authorities, funding, councils, authority, council, county
## Topic 18 Top Words:
## Highest Prob: education, skills, training, young, students, university, college
## FREX: students, apprenticeships, universities, ema, fe, graduates, colleges
## Lift: 16-19, 16-to-19, apostrophe, apprenticeships, as-levels, baccalaureate, co-financed
## Score: students, education, skills, training, young, apprenticeships, universities
## Topic 19 Top Words:
## Highest Prob: schools, school, education, children, teachers, parents, pupils
## FREX: schools, teachers, pupils, sen, academies, ofsted, pupil
## Lift: 11-plus, 26-place, academisation, academised, asperger, authority-maintained, carpetright
## Score: schools, school, teachers, pupils, children, education, parents
## Topic 20 Top Words:
## Highest Prob: transport, london, rail, regional, bus, services, line
## FREX: rail, bus, passengers, fares, railways, hs2, freight
## Lift: 12-car, 15.15, 50.1, a69, adac, adtranz, agglomeration
## Score: rail, transport, bus, passengers, fares, regional, london
## Topic 21 Top Words:
## Highest Prob: police, crime, officers, behaviour, policing, antisocial, community
## FREX: policing, antisocial, graffiti, crime, officers, police, constable
## Lift: asbos, #22k, #29k, 1-2-3, 1,011, 1,075, 1,112
## Score: police, crime, officers, policing, antisocial, behaviour, constable
## Topic 22 Top Words:
## Highest Prob: million, year, budget, cuts, cut, billion, tax
## FREX: obr, budget, millionaires, wage, cuts, cut, billion
## Lift: double-dip, #1,150, 0.38, 0.76p, 1,003, 1,130, 1,196
## Score: tax, cuts, budget, wage, unemployment, chancellor, billion
## Topic 23 Top Words:
## Highest Prob: alcohol, drugs, people, drug, smoking, young, use
## FREX: tobacco, cannabis, cull, tb, palestinians, hamas, pornography
## Lift: #230, #4.5, #600, #700, #no2lgbthate, 0.7p, 1,000-almost

```

```

##      Score: alcohol, smoking, israel, drugs, tobacco, drug, palestinian
## Topic 24 Top Words:
##      Highest Prob: culture, sport, media, football, clubs, arts, club
##      FREX: sport, games, gambling, betting, venues, lap-dancing, touts
##      Lift: betting, casinos, #12, 070, 1-that, 1,000-it, 1,200-i
##      Score: sport, football, arts, tickets, sports, clubs, games
## Topic 25 Top Words:
##      Highest Prob: children, child, care, families, parents, family, carers
##      FREX: csa, same-sex, child, lone, carers, parent, children's
##      Lift: 193,000, aynsley-green, bont, brat, browne-wilkinson, capstick, child-focused
##      Score: child, children, parents, carers, care, families, children's
## Topic 26 Top Words:
##      Highest Prob: planning, land, development, sites, site, national, green
##      FREX: gypsies, gypsy, planning, brownfield, land, sites, co-operative
##      Lift: #tartantories, 1,000-year-old, 1,314, 1,375, 1,500-place, 10-we, 10,996
##      Score: planning, land, sites, site, development, brownfield, museum
## Topic 27 Top Words:
##      Highest Prob: home, secretary, security, inquiry, investigation, office, terrorism
##      FREX: tpims, isc, sfo, reviewer, terrorism, investigations, tpim
##      Lift: intercept, 1,454, 1004, 107674, 11-point, 1141, 124a
##      Score: terrorism, secretary, home, terrorist, police, investigation, tpims
## Topic 28 Top Words:
##      Highest Prob: vote, political, parliament, people, election, parties, elected
##      FREX: electoral, polling, voting, vote, turnout, votes, referendums
##      Lift: voter, @leamingtonsbcb, @maggieannehayes, @nhconsortium, #keeptweeting, 1,166, 1,294
##      Score: vote, electoral, elections, referendum, voting, democracy, political
## Topic 29 Top Words:
##      Highest Prob: benefit, tax, pension, benefits, credit, income, pensions
##      FREX: pension, claimants, pensions, pensioners, allowance, retirement, pensioner
##      Lift: 2046, 25.55, actuarially, benefit-to, benefit's, brethren's, decumulation
##      Score: pension, tax, pensioners, allowance, pensions, credit, income
## Topic 30 Top Words:
##      Highest Prob: one, get, time, going, go, just, know
##      FREX: going, things, get, lot, something, really, go
##      Lift: 1,500-more, 1.37, 10-hours, 10-week-old, 10.65, 100,000-i, 11-month
##      Score: get, going, things, think, told, hours, really
## Topic 31 Top Words:
##      Highest Prob: report, review, year, last, said, response, decision
##      FREX: report, official, published, review, vol, march, july
##      Lift: cayton's, 0.15, 01, 1-2mc, 1-who, 1,033, 1,124,818
##      Score: report, review, published, consultation, official, vol, decision
## Topic 32 Top Words:
##      Highest Prob: people, work, young, many, help, support, need
##      FREX: disabled, people, disability, people's, work, disabilities, job
##      Lift: bip, ciara, dominoes, glencraft, specs, upper-rate, whizz-kidz
##      Score: people, young, disabled, work, disability, youth, employment
## Topic 33 Top Words:
##      Highest Prob: clause, amendment, new, amendments, act, provisions, regulations
##      FREX: nos, clause, clauses, amendments, insert, amendment, affirmative
##      Lift: 153a4, 21-day, 22a, 287, 44a, 4a1, 51b
##      Score: clause, amendment, amendments, nos, insert, clauses, provisions
## Topic 34 Top Words:
##      Highest Prob: cases, law, court, legal, justice, case, criminal
##      FREX: defendants, defendant, court, courts, magistrates, prosecution, offence

```

```

##      Lift: 2,744, 931, 933, acquit, adults-and, anabah, bailiff's
##      Score: court, offence, courts, criminal, offences, rape, prosecution
## Topic 35 Top Words:
##      Highest Prob: international, defence, world, forces, countries, armed, war
##      FREX: military, iraq, humanitarian, veterans, nato, sri, sierra
##      Lift: 2249, 45s, aquis, afghans, alabed, aleppo, asia-pacific
##      Score: un, military, armed, afghanistan, forces, syria, iraq
## Topic 36 Top Words:
##      Highest Prob: financial, money, bank, debt, scheme, banks, credit
##      FREX: loan, lending, payday, fca, lenders, debt, bank
##      Lift: 0.21, 0.33, 0.84, 1,021, 1,413, 1,665, 1,734
##      Score: debt, banks, bank, financial, loan, banking, lending
## Topic 37 Top Words:
##      Highest Prob: debate, members, many, today, us, speech, house
##      FREX: backbench, leader, proud, speak, queen's, speech, privilege
##      Lift: @daisydumble, @percyblakeney63, #neverthelesshepersisted, 1,084, 1.00, 10-government, 10
##      Score: leader, debate, speech, holocaust, house, backbench, members
## Topic 38 Top Words:
##      Highest Prob: public, commission, role, work, new, independent, standards
##      FREX: audit, framework, bodies, commission, accountability, responsibilities, governance
##      Lift: 1,087, 10-seek, 103-4, 108-are, 11-children, 11,076, 1246
##      Score: commission, public, audit, responsibilities, accountability, bodies, auditor
## Topic 39 Top Words:
##      Highest Prob: wales, scotland, scottish, northern, england, ireland, welsh
##      FREX: wales, scotland, scottish, ireland, welsh, snp, scotland's
##      Lift: house16, calman, scotland, 1,009, 1,099, 1,296, 1,333
##      Score: wales, scottish, scotland, welsh, assembly, ireland, northern
## Topic 40 Top Words:
##      Highest Prob: bill, committee, members, legislation, debate, time, hope
##      FREX: committee, bill, select, scrutiny, detail, legislation, debated
##      Lift: 12-minute, guillotined, mdu, noakes, post-legislative, volte, 1080
##      Score: bill, committee, legislation, scrutiny, select, members, committees
## Topic 41 Top Words:
##      Highest Prob: european, uk, eu, union, countries, trade, europe
##      FREX: asylum, nationals, enlargement, treaty, lisbon, immigration, dubs
##      Lift: 2.95, 54,500, anti-european, anti-trust, australian-style, benefitted, buns
##      Score: eu, european, immigration, treaty, asylum, union, europe
## Topic 42 Top Words:
##      Highest Prob: secretary, state, change, climate, industry, green, jobs
##      FREX: solar, flood, steel, state's, climate, renewables, state
##      Lift: solar, #solar, 1-yes, 1,343, 1,528, 1,631, 1,720
##      Score: secretary, state, climate, carbon, flood, steel, emissions
## Topic 43 Top Words:
##      Highest Prob: constituency, city, centre, constituents, area, town, west
##      FREX: petitioners, viston, swindon, humber, hull, petition, burton
##      Lift: ablewell, annesley, bamford's, barwick, binnie, brackla, brancepeth
##      Score: petitioners, constituency, petition, hull, city, town, yorkshire
## Topic 44 Top Words:
##      Highest Prob: can, important, point, take, need, issue, make
##      FREX: point, important, understand, issue, look, different, certainly
##      Lift: advocate-interruption, available-not, cakes-let, change-although, cipfa-a, community-but
##      Score: point, important, issue, issues, decisions, can, want
## Topic 45 Top Words:
##      Highest Prob: house, question, order, move, mr, speaker, put

```

```
##      FREX: question, lords, beg, motion, speaker, house, agrees
##      Lift: closurestanding, 1,142,600, 10.00, 109b, 11.00, 135wh, 14f2
##      Score: house, lords, speaker, mr, question, motion, deputy
```

2.6.3 Full topic model estimate summary - k45

```
##
## Call:
## estimateEffect(formula = 1:45 ~ short_list, stmobj = topic_model_k45,
##      metadata = lab_corpus_fem_stm$meta, uncertainty = "Global")
##
##
## Topic 1:
##
## Coefficients:
##      Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0204923  0.0004400  46.575 < 0.0000000000000002 ***
## short_listTRUE -0.0027720  0.0005738  -4.831      0.00000136 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 2:
##
## Coefficients:
##      Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.011165568  0.000375567  29.730 <0.0000000000000002 ***
## short_listTRUE -0.000002311  0.000443109  -0.005      0.996
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##      Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0181563  0.0003821  47.521 <0.0000000000000002 ***
## short_listTRUE 0.0010525  0.0004718   2.231      0.0257 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##      Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0188143  0.0005121  36.741 <0.0000000000000002 ***
## short_listTRUE -0.0002318  0.0006494  -0.357      0.721
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 5:
```

```

##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0155127  0.0005317  29.173 < 0.0000000000000002 ***
## short_listTRUE 0.0041749  0.0006677   6.252    0.000000000406 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 6:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0369175  0.0003549 104.026 < 0.0000000000000002 ***
## short_listTRUE 0.0019923  0.0004479   4.448    0.00000868 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0193282  0.0002811  68.75 < 0.0000000000000002 ***
## short_listTRUE -0.0015250  0.0003397  -4.49    0.00000714 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 8:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0088747  0.0003904  22.73 < 0.0000000000000002 ***
## short_listTRUE 0.0056277  0.0005603  10.04 < 0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 9:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0098222  0.0003688  26.633 < 0.0000000000000002 ***
## short_listTRUE 0.0004864  0.0004481   1.085    0.278
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0216361  0.0005577  38.794 < 0.0000000000000002 ***

```

```

## short_listTRUE -0.0047395  0.0006864  -6.905      0.000000000000507 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0315920  0.0004287  73.700 < 0.0000000000000002 ***
## short_listTRUE 0.0032161  0.0005285   6.085      0.00000000117 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 12:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0346217  0.0007047  49.126 < 0.0000000000000002 ***
## short_listTRUE -0.0072007  0.0009219  -7.811  0.00000000000000575 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0116989  0.0003660  31.97 < 0.0000000000000002 ***
## short_listTRUE 0.0062268  0.0005053  12.32 < 0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0170237  0.0004612  36.912 < 0.0000000000000002 ***
## short_listTRUE -0.0032559  0.0006147  -5.296      0.000000118 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0166958  0.0003665  45.558 < 0.0000000000000002 ***
## short_listTRUE -0.0011846  0.0004415  -2.683      0.00729 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

```

```

##
## Topic 16:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0254956   0.0004391   58.06 <0.0000000000000002 ***
## short_listTRUE -0.0092996   0.0005127  -18.14 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 17:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0259246   0.0004060   63.86 <0.0000000000000002 ***
## short_listTRUE -0.0055131   0.0005061  -10.89 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0177193   0.0004511   39.282 <0.0000000000000002 ***
## short_listTRUE 0.0004214   0.0005448    0.773      0.439
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 19:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0165322   0.0005373   30.767 < 0.0000000000000002 ***
## short_listTRUE 0.0039421   0.0006520    6.047      0.00000000149 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0181362   0.0005760   31.485 < 0.0000000000000002 ***
## short_listTRUE 0.0038855   0.0006755    5.752      0.00000000887 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:

```

```

##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0240600  0.0006096   39.47 <0.0000000000000002 ***
## short_listTRUE -0.0061955  0.0007246   -8.55 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 22:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0362013  0.0006487   55.80 <0.0000000000000002 ***
## short_listTRUE 0.0099907  0.0008439   11.84 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 23:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0131289  0.0005690   23.072 <0.0000000000000002 ***
## short_listTRUE 0.0015221  0.0006459    2.356    0.0185 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0082573  0.0003679   22.446 <0.0000000000000002 ***
## short_listTRUE 0.0039146  0.0004544    8.614 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 25:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0201211  0.0004828   41.674 <0.0000000000000002 ***
## short_listTRUE 0.0008841  0.0005839    1.514    0.13
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0117376  0.0003719   31.563 < 0.0000000000000002 ***
## short_listTRUE -0.0017063  0.0004565   -3.738    0.000186 ***
## ---

```



```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0214030  0.0004861   44.03 <0.0000000000000002 ***
## short_listTRUE -0.0059876  0.0005921  -10.11 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 28:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0143836  0.0004510  31.891 < 0.0000000000000002 ***
## short_listTRUE 0.0031514  0.0005626   5.602    0.0000000213 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0198913  0.0005719   34.78 <0.0000000000000002 ***
## short_listTRUE 0.0087452  0.0007086   12.34 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 30:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0396837  0.0003924  101.13 <0.0000000000000002 ***
## short_listTRUE 0.0072101  0.0004853   14.86 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 31:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0327870  0.0004275   76.689 <0.0000000000000002 ***
## short_listTRUE 0.0010281  0.0005388    1.908    0.0564 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 32:

```

```

##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0267156  0.0003250  82.194 < 0.0000000000000002 ***
## short_listTRUE 0.0015659  0.0004073   3.844   0.000121 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 33:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0272176  0.0005596  48.638 <0.0000000000000002 ***
## short_listTRUE -0.0056695  0.0006418  -8.834 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 34:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0323327  0.0005795  55.79 <0.0000000000000002 ***
## short_listTRUE -0.0127423  0.0007108 -17.93 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 35:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0283386  0.0007050  40.197 <0.0000000000000002 ***
## short_listTRUE -0.0010477  0.0008671  -1.208   0.227
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 36:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0157149  0.0003754  41.856 < 0.0000000000000002 ***
## short_listTRUE 0.0015127  0.0004898   3.088   0.00201 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 37:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0236912  0.0003741  63.32 <0.0000000000000002 ***

```

```

## short_listTRUE 0.0061847 0.0004956 12.48 <0.0000000000000002 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 38:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0280904  0.0003831   73.32 <0.0000000000000002 ***
## short_listTRUE -0.0065547  0.0005153  -12.72 <0.0000000000000002 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 39:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0109060  0.0003865   28.219 < 0.0000000000000002 ***
## short_listTRUE 0.0038260  0.0004990    7.667  0.0000000000000177 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 40:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0285248  0.0004119   69.253 <0.0000000000000002 ***
## short_listTRUE 0.0009335  0.0004711    1.982      0.0475 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 41:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0259833  0.0005491   47.321 < 0.0000000000000002 ***
## short_listTRUE -0.0052597  0.0006576   -7.998  0.00000000000000128 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 42:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0168726  0.0004341   38.87 <0.0000000000000002 ***
## short_listTRUE 0.0083565  0.0005823   14.35 <0.0000000000000002 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

```

```
##
## Topic 43:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0132674  0.0003974   33.38 <0.0000000000000002 ***
## short_listTRUE 0.0070829  0.0005321   13.31 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 44:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0676797  0.0004252  159.19 <0.0000000000000002 ***
## short_listTRUE -0.0154071  0.0005316  -28.98 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 45:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0168149  0.0003048   55.170 <0.0000000000000002 ***
## short_listTRUE -0.0005857  0.0003797   -1.543      0.123
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

3 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 gender distinction in some selected terms and topics. AWS MPs are far more likely to make reference to their constituency and their 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 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, then 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:

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?

4 Appendix

4.1 K30

4.2 K30

4.2.1 Shortlists vs Non-Shortlists - K30

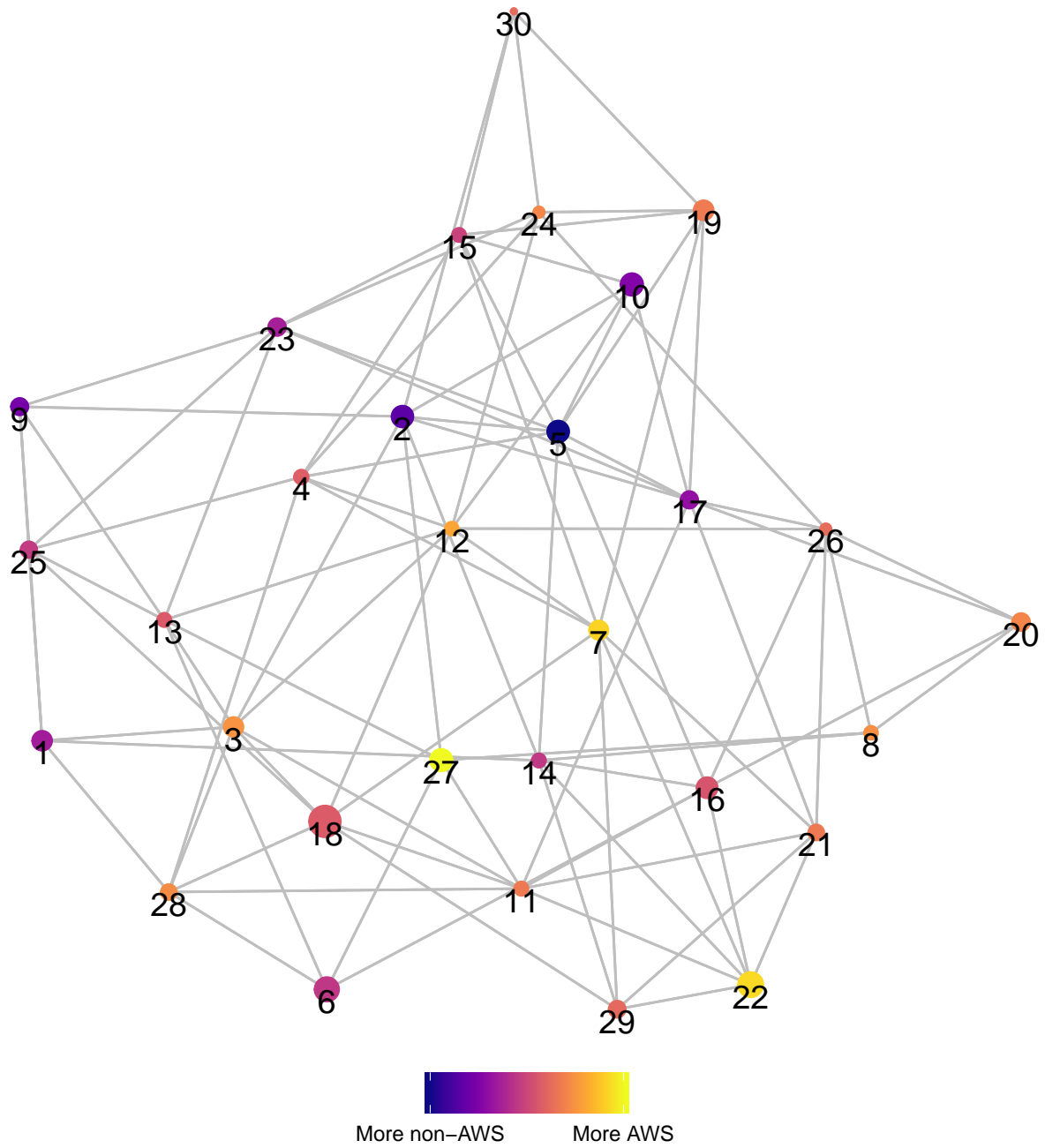


Figure 11: Fruchterman-Reingold plot of K30 Network

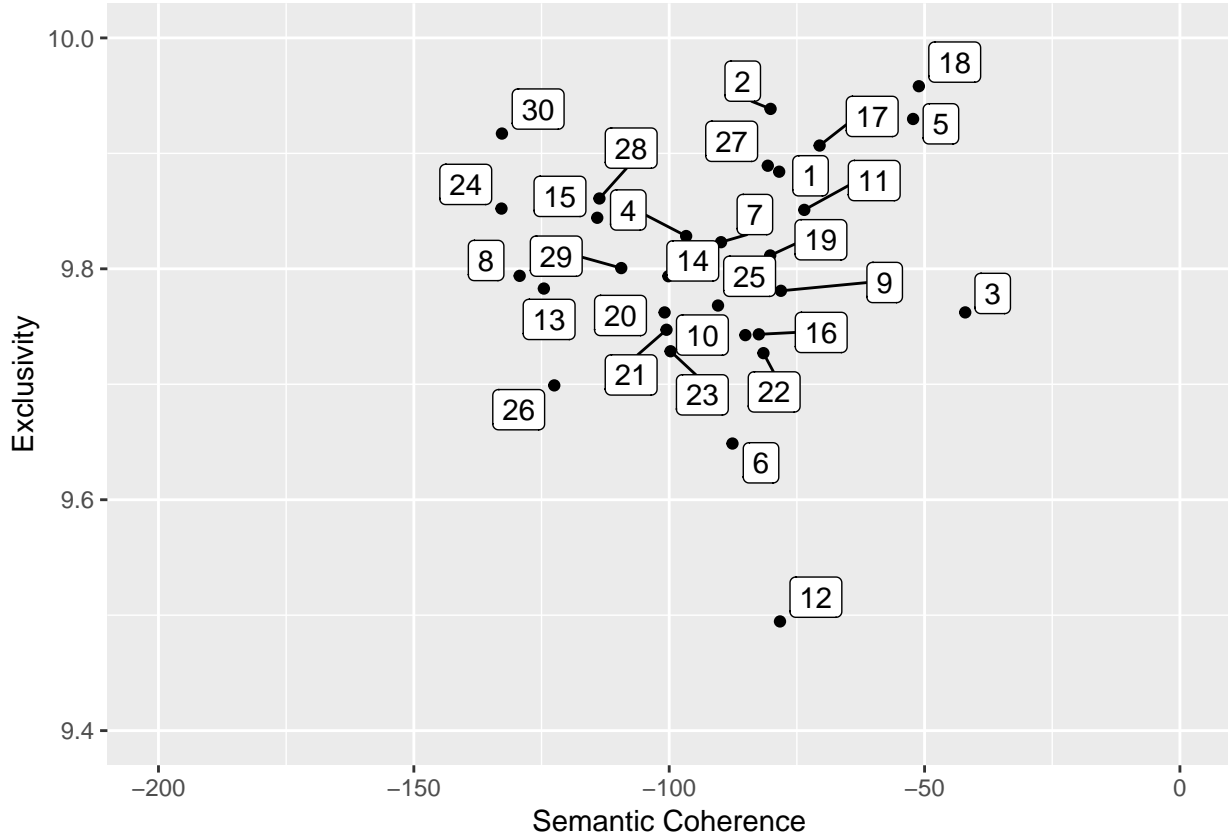


Figure 12: Coherence of K30 Topic Models

In all but five topics (gender, immigration, international, children and the environment) the model found p values of < 0.01 , and in every topic except the aforementioned and “people”, p values of < 0.001 .

Table 13: Topic Estimates

	Estimate	Standard Error	t value	Pr(> t)	
Topic 1 – Bills					
Intercept	0.0458794	0.0006737	68.0957190	< 0.001	***
Shortlist	-0.0075246	0.0008285	-9.0825064	< 0.001	***
Topic 2 – Consultations					
Intercept	0.0649519	0.0005432	119.5623054	< 0.001	***
Shortlist	-0.0140286	0.0006206	-22.6031765	< 0.001	***
Topic 3 – Members					
Intercept	0.0399431	0.0005129	77.8751400	< 0.001	***
Shortlist	0.0062751	0.0006495	9.6616626	< 0.001	***
Topic 4 – Gender					
Intercept	0.0221355	0.0005885	37.6147530	< 0.001	***
Shortlist	0.0005980	0.0006905	0.8660352	0.39	
Topic 5 – Civic society					
Intercept	0.0713560	0.0005553	128.5076236	< 0.001	***
Shortlist	-0.0196442	0.0006423	-30.5842072	< 0.001	***
Topic 6 – International					

Table 13: Topic Estimates (*continued*)

	Estimate	Standard Error	t value	Pr(> t)	
Intercept	0.0459938	0.0008900	51.6809222	< 0.001	***
Shortlist	-0.0041425	0.0011070	-3.7420418	< 0.001	***
Topic 7 – Disability					
Intercept	0.0268198	0.0005580	48.0664294	< 0.001	***
Shortlist	0.0121329	0.0007551	16.0682059	< 0.001	***
Topic 8 – Rural Issues					
Intercept	0.0141969	0.0004710	30.1433030	< 0.001	***
Shortlist	0.0060397	0.0006063	9.9614964	< 0.001	***
Topic 9 – Immigration					
Intercept	0.0364707	0.0006405	56.9404072	< 0.001	***
Shortlist	-0.0116370	0.0007510	-15.4959912	< 0.001	***
Topic 10 – Health Care					
Intercept	0.0435419	0.0007459	58.3748229	< 0.001	***
Shortlist	-0.0103309	0.0009316	-11.0892120	< 0.001	***
Topic 11 – Parties					
Intercept	0.0318511	0.0004340	73.3835860	< 0.001	***
Shortlist	0.0036476	0.0005764	6.3279440	< 0.001	***
Topic 12 – Constituencies					
Intercept	0.0224519	0.0005094	44.0722556	< 0.001	***
Shortlist	0.0080774	0.0006397	12.6263783	< 0.001	***
Topic 13 – Security					
Intercept	0.0229242	0.0005050	45.3978800	< 0.001	***
Shortlist	-0.0000191	0.0006097	-0.0312658	0.98	
Topic 14 – Investment					
Intercept	0.0262786	0.0005320	49.3991764	< 0.001	***
Shortlist	-0.0039558	0.0006504	-6.0825011	< 0.001	***
Topic 15 – Youth					
Intercept	0.0229408	0.0005608	40.9083981	< 0.001	***
Shortlist	-0.0027445	0.0006821	-4.0237095	< 0.001	***
Topic 16 – Energy					
Intercept	0.0358256	0.0007009	51.1123049	< 0.001	***
Shortlist	-0.0005270	0.0009097	-0.5792854	0.56	
Topic 17 – Local authorities					
Intercept	0.0398888	0.0005064	78.7671803	< 0.001	***
Shortlist	-0.0089574	0.0006054	-14.7956775	< 0.001	***
Topic 18 – People					
Intercept	0.0846647	0.0005588	151.5087012	< 0.001	***
Shortlist	0.0003543	0.0007028	0.5041368	0.61	
Topic 19 – Education					
Intercept	0.0282583	0.0007112	39.7321428	< 0.001	***
Shortlist	0.0038545	0.0008330	4.6273894	< 0.001	***
Topic 20 – Transport					
Intercept	0.0228147	0.0006004	38.0008577	< 0.001	***
Shortlist	0.0049505	0.0007871	6.2896634	< 0.001	***
Topic 21 – Housing					
Intercept	0.0202325	0.0005989	33.7836920	< 0.001	***

Table 13: Topic Estimates (*continued*)

	Estimate	Standard Error	t value	Pr(> t)	
Shortlist	0.0037259	0.0007071	5.2691947	< 0.001	***
Topic 22 – Tax					
Intercept	0.0440552	0.0008160	53.9881493	< 0.001	***
Shortlist	0.0126968	0.0010408	12.1995253	< 0.001	***
Topic 23 – Police					
Intercept	0.0300345	0.0005987	50.1690133	< 0.001	***
Shortlist	-0.0070610	0.0007797	-9.0558590	< 0.001	***
Topic 24 – Media					
Intercept	0.0112197	0.0004428	25.3383197	< 0.001	***
Shortlist	0.0049879	0.0005054	9.8686912	< 0.001	***
Topic 25 – Families					
Intercept	0.0258003	0.0006233	41.3947868	< 0.001	***
Shortlist	-0.0035715	0.0007971	-4.4806398	< 0.001	***
Topic 26 – Environment					
Intercept	0.0145392	0.0004340	33.5042303	< 0.001	***
Shortlist	0.0022641	0.0005689	3.9799482	< 0.001	***
Topic 27 – Ministers					
Intercept	0.0419257	0.0005334	78.5944949	< 0.001	***
Shortlist	0.0151665	0.0006891	22.0086393	< 0.001	***
Topic 28 – Regions					
Intercept	0.0228762	0.0005294	43.2155294	< 0.001	***
Shortlist	0.0055453	0.0006889	8.0489028	< 0.001	***
Topic 29 – Pensions					
Intercept	0.0265453	0.0005796	45.7970638	< 0.001	***
Shortlist	0.0017446	0.0007317	2.3844040	0.017	*
Topic 30 – Technology					
Intercept	0.0135814	0.0003310	41.0349550	< 0.001	***
Shortlist	0.0020713	0.0004224	4.9040129	< 0.001	***

Table 14: Distribution of Topics Among Female Labour MPs – K30

Topic	One or more speeches	Five or more speeches
Bills	138	82
Health Care	157	117
Parties	141	87
Constituencies	162	100
Security	145	69
Investment	129	67
Youth	142	73
Energy	157	124
Local authorities	151	100
People	165	146
Education	153	115
Consultations	156	107
Transport	157	102

Table 14: Distribution of Topics Among Female Labour MPs – K30
(continued)

Topic	One or more speeches	Five or more speeches
Housing	145	74
Tax	159	131
Police	151	97
Media	136	68
Families	149	94
Environment	131	63
Ministers	163	139
Regions	138	86
Pensions	143	92
Members	153	104
Technology	127	48
Gender	153	90
Civic society	157	118
International	163	137
Disability	155	119
Rural Issues	141	80
Immigration	147	84

There is no topic that every single female Labour MP has discussed at least once. The most widely used is the topic “People”, which out of 167 female Labour MPs in the dataset, 16 500% made at least one speech in that topic. 88.5% of those MPs made five or more speeches about “People”.

Table 15: Count and Distribution of Topics – K30

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
Bills	1,819	3.38%	1,263	4.53%	8,176	4.83%
Consultations	1,997	3.71%	1,824	6.55%	9,027	5.33%
Members	2,146	3.99%	844	3.03%	8,694	5.13%
Gender	1,039	1.93%	553	1.98%	882	0.52%
Civic society	2,050	3.81%	1,838	6.6%	7,616	4.5%
International	3,138	5.83%	1,892	6.79%	13,834	8.17%
Disability	2,266	4.21%	601	2.16%	2,787	1.65%
Rural Issues	1,043	1.94%	366	1.31%	2,370	1.4%
Immigration	1,197	2.23%	1,073	3.85%	4,655	2.75%
Health Care	2,382	4.43%	1,780	6.39%	4,728	2.79%
Parties	1,004	1.87%	497	1.78%	4,055	2.39%
Constituencies	1,029	1.91%	370	1.33%	2,897	1.71%
Security	1,002	1.86%	501	1.8%	2,810	1.66%
Investment	852	1.58%	632	2.27%	3,098	1.83%
Youth	884	1.64%	582	2.09%	1,323	0.78%
Energy	2,339	4.35%	1,188	4.26%	7,621	4.5%
Local authorities	1,316	2.45%	988	3.55%	4,371	2.58%
People	6,346	11.8%	2,922	10.49%	30,543	18.04%

Table 15: Count and Distribution of Topics – K30 (*continued*)

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
Education	2,187	4.07%	936	3.36%	4,801	2.84%
Transport	1,769	3.29%	689	2.47%	4,882	2.88%
Housing	1,319	2.45%	540	1.94%	2,058	1.22%
Tax	3,968	7.38%	1,422	5.1%	10,953	6.47%
Police	1,425	2.65%	971	3.48%	3,523	2.08%
Media	762	1.42%	256	0.92%	2,050	1.21%
Families	1,271	2.36%	791	2.84%	1,112	0.66%
Environment	712	1.32%	282	1.01%	1,706	1.01%
Ministers	3,158	5.87%	921	3.31%	8,380	4.95%
Regions	1,421	2.64%	441	1.58%	6,218	3.67%
Pensions	1,445	2.69%	723	2.59%	3,022	1.78%
Technology	502	0.93%	177	0.64%	1,149	0.68%

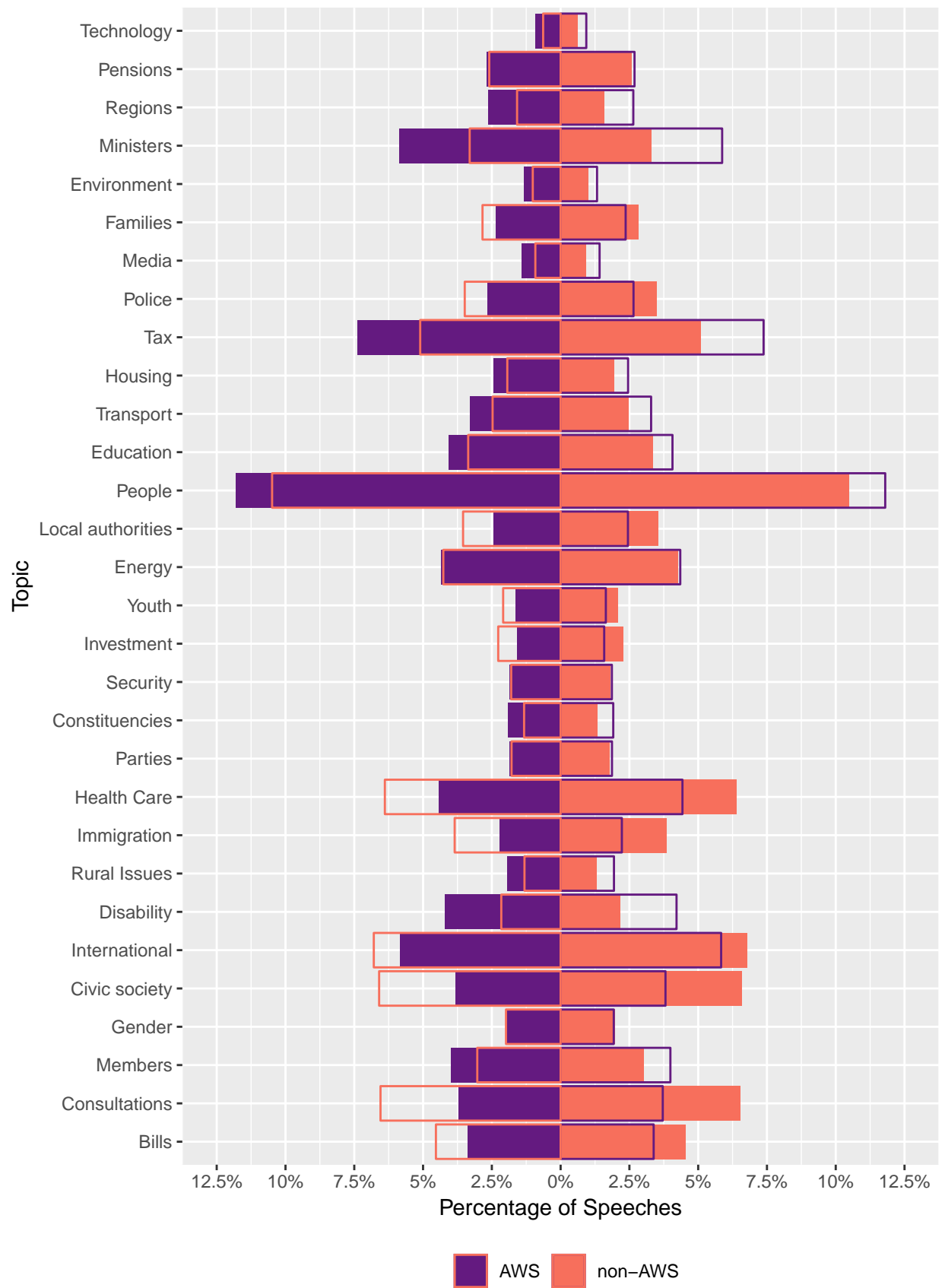


Figure 13: K30 Pyramid Chart

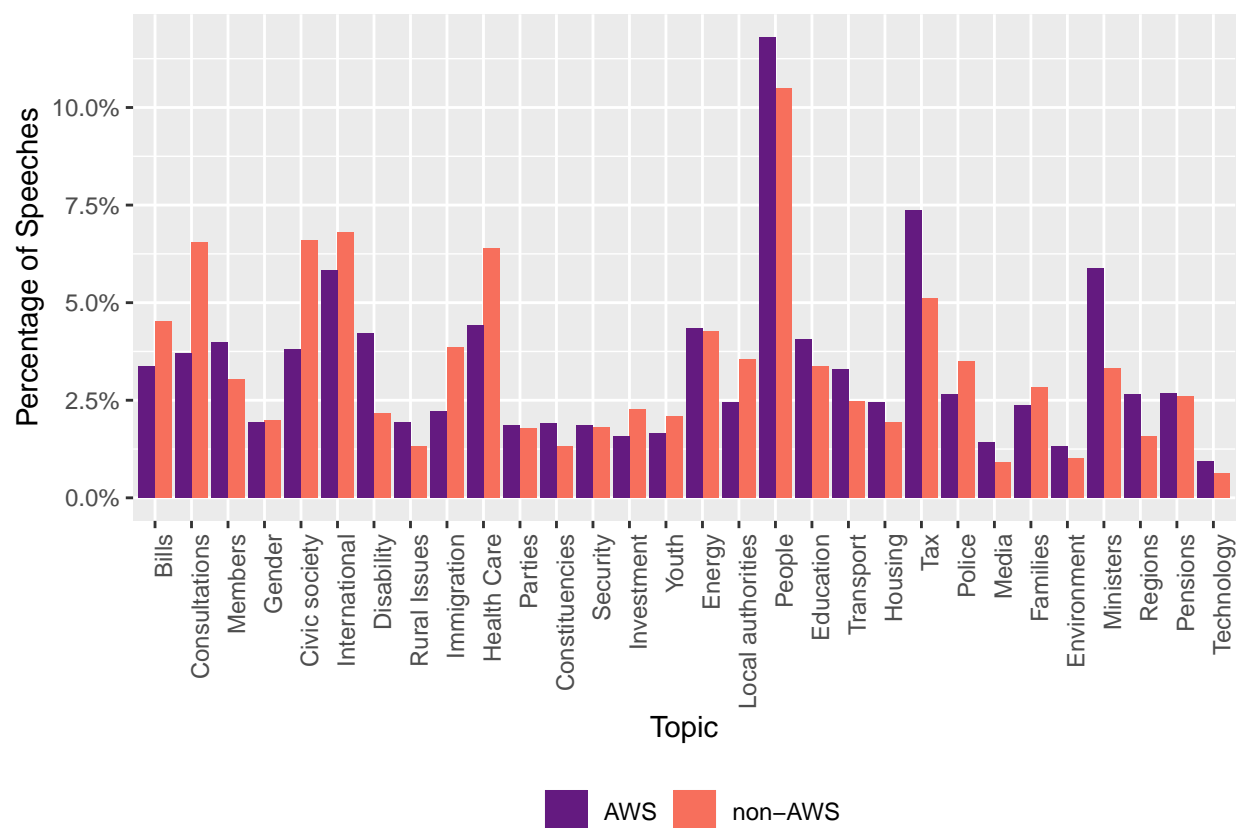


Figure 14: K30 Bar Chart

AWS are – proportionally – more likely than non-AWS MPs to discuss Topics 29 (parliament), 7 (disability) and 24 (media). They are proportionally less likely to mention Topics 15 (justice), 2 (consultations) and 9 (disease). See Figure 15 for more details. Perhaps surprisingly, AWS MPs are slightly less likely to mention gender issues (Topic 3), although the difference is not statistically significant (see the appendix for details).

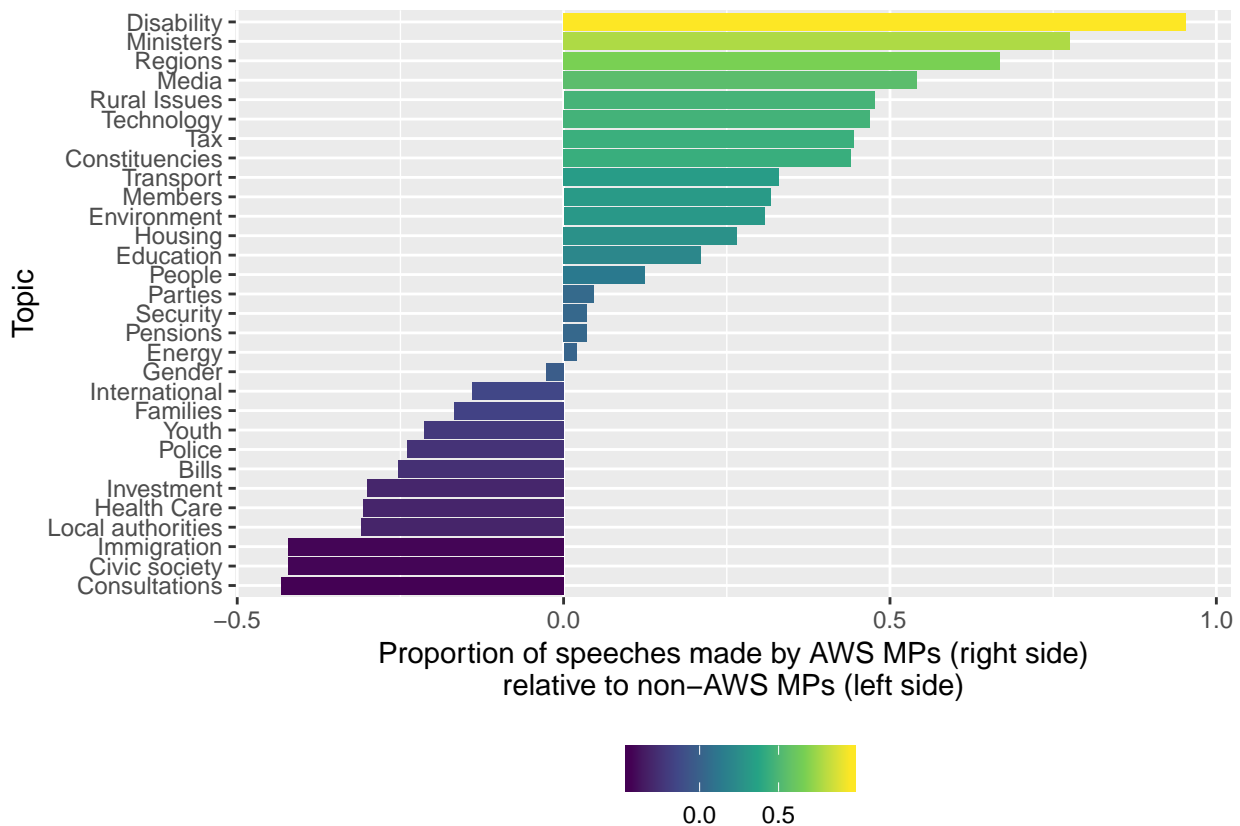


Figure 15: K30 Topic Proportions

4.2.1.1 Word Occurences

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).

Table 16: Words in Topic - K30

Topic Number	Top Ten Words	Top Ten FREX
Topic 1	bill, clause, amendment, new, legislation, amendments, act, committee, provisions, regulations, powers, government, place, provision, lords, power, 1, house, order, section	clause, amendment, amendments, clauses, nos, insert, provisions, bill, regulations, tabled, bill's, schedule, affirmative, section, lords, legislation, passage, drafted, draft, beg
Topic 2	made, report, review, information, issue, issues, concerns, process, matter, consultation, consider, taken, whether, aware, raised, clear, take, evidence, point, however	review, consultation, guidance, recommendations, published, concerns, assessment, considering, raised, representations, specific, matter, report, detailed, considered, indicated, raises, process, consideration, details
Topic 3	member, members, debate, house, committee, said, made, many, time, issues, today, issue, important, also, heard, hope, speech, opportunity, us, support	member, debates, select, debate, backbench, sides, spoke, thoughtful, back-bench, westmr, remarks, debating, members, comments, northmr, southmr, eastmr, speeches, tone, eloquently

Table 16: Words in Topic - K30 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 4	women, men, pay, rights, equality, women's, discrimination, equal, society, gender, many, woman, age, charities, human, girls, commission, ethnic, church, work	women, equality, gender, discrimination, female, equal, women's, ethnic, bishops, equalities, men, religion, church, shortlists, male, religious, all-women, asian, race, girls
Topic 5	work, ensure, important, can, need, support, public, service, also, new, must, working, make, role, services, national, welcome, organisations, provide, good	ensure, ensuring, organisations, important, role, voluntary, together, range, steps, closely, improve, framework, progress, friend's, ways, expertise, approach, effective, departments, best
Topic 6	european, countries, eu, international, uk, world, british, union, europe, defence, trade, foreign, united, forces, country, states, government, rights, us, human	military, refugees, humanitarian, israel, troops, palestinian, russia, israeli, gaza, nato, zimbabwe, syrian, burma, iraqi, accession, russian, enlargement, wto, yemen, daesh
Topic 7	people, work, care, support, benefit, employment, disabled, social, carers, working, benefits, workers, many, help, employers, families, hours, job, disability, get	disabled, jobcentre, incapacity, carers, esa, dla, carer's, atos, dwp, lone, disability, claimants, remploy, zero-hours, employers, caring, pip, disabilities, jobcentres, employment
Topic 8	food, post, office, rural, petition, offices, farmers, waste, royal, constituency, mail, closure, petitioners, government, many, products, house, residents, areas, therefore	petition, farmers, petitioners, meat, cull, tb, labelling, badgers, badger, bovine, beef, culling, sub-post, gm, dairy, sub-postmasters, mail, vegetables, cattle, poultry
Topic 9	cases, legal, law, court, case, justice, rights, act, courts, system, immigration, criminal, offence, human, appeal, can, person, civil, asylum, complaints	fur, attorney-general, mink, asylum, immigration, sfo, magistrates, sia, appeal, appeals, lawyers, legal, dogs, fraud, dog, court, extradition, judges, courts, seekers
Topic 10	health, nhs, care, services, patients, hospital, cancer, service, treatment, medical, staff, trust, hospitals, patient, doctors, trusts, primary, research, year, nurses	patients, cancer, patient, clinical, gps, gp, dentists, dental, pct, pcts, dementia, clinicians, dentistry, flu, embryos, dentist, palliative, prostate, cervical, hepatitis
Topic 11	government, labour, conservative, party, policy, government's, opposition, public, previous, years, liberal, cuts, conservatives, tory, members, policies, proposals, now, country, hull	liberal, democrats, conservatives, conservative, tory, tories, democrat, lib, hull, manifesto, coalition, labour, benches, promises, party's, party, pledge, rhetoric, abolish, promise
Topic 12	constituency, people, years, many, constituents, one, day, life, first, proud, work, now, like, family, great, city, lives, south, just, two	helier, maiden, salford, st, burnley, merton, mp, halifax, mitcham, miners, famous, trafford, mum, honour, morden, proud, pride, jo, dad, hackney
Topic 13	mr, speaker, order, security, home, deputy, terrorism, threat, fire, safety, control, emergency, investigation, intelligence, orders, terrorist, put, evidence, risk, attacks	sri, tpims, firefighters, isc, lankan, tpim, intercept, proscription, terrorist, yarl's, proscribed, extremism, terrorists, detainees, tamil, terrorism, lanka, mr, fire, speaker

Table 16: Words in Topic - K30 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 14	companies, financial, company, market, business, public, bank, competition, regulation, sector, industry, banks, insurance, interest, consumers, accounts, private, treasury, regulatory, services	liabilities, policyholders, penrose, shareholders, regulators, auditor, accounting, competition, banking, oft, nao, corporate, comptroller, profits, shares, fsa, equitable, company's, cdc, rbs
Topic 15	young, people, health, mental, youth, prison, drug, drugs, problems, age, services, 16, treatment, community, offenders, prisons, prisoners, can, suicide, use	prisons, probation, cannabis, reoffending, mental, self-harm, drug, prison, youth, drugs, young, prisoners, psychoactive, suicides, suicide, offending, psychiatric, rehabilitation, keynes, milton
Topic 16	jobs, businesses, business, investment, economy, industry, energy, economic, new, small, growth, uk, future, change, climate, sector, government, skills, development, support	manufacturing, renewable, renewables, solar, low-carbon, carbon, onshore, climate, nissan, flood, steel, oil, biofuels, wind, emissions, businesses, apprentices, enterprise, energy-intensive, economy
Topic 17	local, authorities, funding, areas, council, services, authority, community, area, communities, money, councils, million, new, social, needs, resources, fund, regional, planning	local, authorities, councils, funding, authority, formula, grant, areas, county, councillors, deprived, locally, council, allocated, allocation, partnerships, deprivation, surrey, lancashire, partnership
Topic 18	people, want, one, can, get, say, know, think, us, make, many, need, go, time, much, just, see, point, said, take	things, think, say, something, want, going, get, lot, go, thing, trying, talking, really, saying, absolutely, quite, might, difficult, come, bit
Topic 19	children, schools, education, school, child, parents, teachers, children's, training, skills, learning, needs, young, pupils, educational, care, special, provision, primary, good	teachers, pupils, curriculum, sen, academies, ofsted, pupil, grammar, attainment, vocational, classroom, fe, gcse, gcse, schools, autism, dyslexia, school, academy, educational
Topic 20	transport, rail, bus, london, road, travel, line, services, network, train, air, passengers, service, traffic, new, roads, station, car, north, fares	rail, bus, passengers, trains, buses, passenger, airports, heathrow, congestion, railways, hs2, freight, high-speed, electrification, crossrail, franchising, commuters, cod, gatwick, tolls
Topic 21	housing, homes, london, private, people, home, social, affordable, accommodation, need, sector, property, rent, properties, tenants, many, council, new, building, landlords	housing, properties, tenants, landlords, rented, homelessness, homeless, rents, tenant, tenancies, tenancy, rent, landlord, homes, two-bedroom, renting, accommodation, affordable, leaseholders, hmos
Topic 22	tax, year, million, budget, increase, billion, cut, cuts, chancellor, government, poverty, rate, pay, impact, families, cost, years, spending, figures, last	vat, obr, millionaires, 50p, deficit, budget, tax, fiscal, billion, chancellor, inflation, rate, hit, cut, credits, rising, chancellor's, borrowing, unemployment, poverty

Table 16: Words in Topic - K30 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 23	police, crime, officers, behaviour, policing, home, people, antisocial, tackle, community, force, serious, powers, number, action, use, alcohol, forces, communities, smoking	policing, constable, gangs, dubs, tobacco, pcsos, crime, asbos, soca, antisocial, drinking, sunbeds, officers, police, gang, sunbed, graffiti, smoking, constabulary, behaviour
Topic 24	bbc, sport, media, culture, football, arts, club, clubs, sports, radio, television, many, creative, games, licence, music, tickets, cultural, events, event	bbc, sports, radio, games, olympic, gambling, bbc's, broadcasting, hove, betting, lap-dancing, touts, sport, fans, arts, music, casinos, copyright, creative, football
Topic 25	children, child, violence, victims, domestic, abuse, family, sexual, families, cases, protection, home, parents, support, vulnerable, many, rape, marriage, justice, one	abortion, csa, same-sex, rape, adoptive, adopters, barring, marriage, sexual, marriages, victims, abuse, survivors, adoption, violence, cafcass, trafficked, domestic, grooming, couples
Topic 26	planning, land, development, site, water, plymouth, sites, environment, area, many, marine, town, buildings, national, one, environmental, building, also, green, new	forestry, gypsies, habitats, gypsy, memorials, marine, woodland, conservation, plymouth, wilberforce, mmo, gospels, museum, vellum, nppf, biodiversity, site, hectares, open-cast, forests
Topic 27	secretary, state, house, last, statement, given, answer, said, thank, now, tell, department, may, ministers, week, today, question, home, can, office	secretary, statement, answer, confirm, state, reply, official, vol, state's, tell, minister's, urgent, yesterday, please, answers, questions, written, announcement, departmental, november
Topic 28	parliament, wales, scotland, vote, scottish, political, northern, ireland, commission, welsh, people, assembly, election, elected, house, referendum, england, parties, elections, one	scottish, electoral, polling, voting, ireland, vote, scotland, hereditary, referendum, referendums, welsh, devolution, assembly, voter, votes, elections, gibraltar, wales, snp, registration
Topic 29	scheme, pension, credit, people, energy, pensions, pensioners, money, debt, pay, savings, income, bills, payments, fuel, schemes, costs, help, advice, payment	pension, payday, pensioners, prepayment, retirement, savings, debt, pensioner, saving, pensions, bills, payments, ofgem, lenders, payment, loan, means-testing, credit, scheme, winter
Topic 30	access, research, data, information, students, university, technology, science, fees, online, higher, internet, use, universities, student, mobile, digital, government, study, website	broadband, data, electronic, student, internet, online, universities, superfast, mobile, computer, students, science, university, fees, mesothelioma, pornography, graduates, technology, degrees, tuition

4.2.2 Full topic model summary - K30

A topic model with 30 topics, 81651 documents and a 119586 word dictionary.

Topic 1 Top Words:

```

## Highest Prob: bill, clause, amendment, new, legislation, amendments, act
## FREX: clause, amendment, amendments, clauses, nos, insert, provisions
## Lift: #185, #85, 0.003, 05, 1-competences, 1-impact, 1,924
## Score: clause, amendment, amendments, bill, provisions, lords, nos
## Topic 2 Top Words:
## Highest Prob: made, report, review, information, issue, issues, concerns
## FREX: review, consultation, guidance, recommendations, published, concerns, assessment
## Lift: 01, 1-who, 1,595, 115661, 118127, 14,940, 152w
## Score: consultation, information, guidance, review, assessment, report, process
## Topic 3 Top Words:
## Highest Prob: member, members, debate, house, committee, said, made
## FREX: member, debates, select, debate, backbench, sides, spoke
## Lift: barracking, dg, dydd, guillotined, gwyl, islesmr, jopling
## Score: member, committee, members, debate, house, opposition, select
## Topic 4 Top Words:
## Highest Prob: women, men, pay, rights, equality, women's, discrimination
## FREX: women, equality, gender, discrimination, female, equal, women's
## Lift: 1871, 744,000, 77p, abbess, aid-style, anti-cancer, bachelet's
## Score: women, women's, equality, men, discrimination, gender, girls
## Topic 5 Top Words:
## Highest Prob: work, ensure, important, can, need, support, public
## FREX: ensure, ensuring, organisations, important, role, voluntary, together
## Lift: 101998, 112172, 120517, 153306, 1998.84161, 2,128, 27591
## Score: work, service, important, sector, services, ensure, organisations
## Topic 6 Top Words:
## Highest Prob: european, countries, eu, international, uk, world, british
## FREX: military, refugees, humanitarian, israel, troops, palestinian, russia
## Lift: aleppo, congo, daesh, #420, #84.3, #87.2, #aleppo
## Score: eu, european, countries, un, military, foreign, syria
## Topic 7 Top Words:
## Highest Prob: people, work, care, support, benefit, employment, disabled
## FREX: disabled, jobcentre, incapacity, carers, esa, dla, carer's
## Lift: 0300, 1-to-1, 1,030, 1,052, 1,366, 1,482, 1,500-more
## Score: carers, disabled, care, disability, allowance, people, wage
## Topic 8 Top Words:
## Highest Prob: food, post, office, rural, petition, offices, farmers
## FREX: petition, farmers, petitioners, meat, cull, tb, labelling
## Lift: sub-post, #210, #450, 00, 0157, 1-tonne, 1,000-year
## Score: food, farmers, petitioners, petition, rural, post, cull
## Topic 9 Top Words:
## Highest Prob: cases, legal, law, court, case, justice, rights
## FREX: fur, attorney-general, mink, asylum, immigration, sfo, magistrates
## Lift: snares, 0.037, 0.044, 1-sale, 1,000-for, 1,000-to, 1,033
## Score: court, offence, courts, criminal, prosecution, immigration, legal
## Topic 10 Top Words:
## Highest Prob: health, nhs, care, services, patients, hospital, cancer
## FREX: patients, cancer, patient, clinical, gps, gp, dentists
## Lift: dentists, embryonic, endometriosis, pandemic, @cfaware, #20, #500
## Score: nhs, patients, health, cancer, hospital, care, patient
## Topic 11 Top Words:
## Highest Prob: government, labour, conservative, party, policy, government's, opposition
## FREX: liberal, democrats, conservatives, conservative, tory, tories, democrat
## Lift: lib, 0.37, 1,009, 1,220, 1,333, 1,608, 1,814
## Score: conservative, government, labour, party, liberal, conservatives, tory

```

```

## Topic 12 Top Words:
## Highest Prob: constituency, people, years, many, constituents, one, day
## FREX: helier, maiden, salford, st, burnley, merton, mp
## Lift: balham, harlesden, helier, 0.27, 0.51, 1,000-square-feet, 1,060
## Score: constituency, helier, maiden, salford, city, constituents, st
## Topic 13 Top Words:
## Highest Prob: mr, speaker, order, security, home, deputy, terrorism
## FREX: sri, tpims, firefighters, isc, lankan, tpim, intercept
## Lift: 1998designated, 83e, abscond, absconded, al-mansour, amir, amna
## Score: mr, terrorism, speaker, terrorist, detention, sri, tpims
## Topic 14 Top Words:
## Highest Prob: companies, financial, company, market, business, public, bank
## FREX: liabilities, policyholders, penrose, shareholders, regulators, auditor, accounting
## Lift: bnfl's, cd fi, securitisation, liabilities, ofwat, rbs, #1.8
## Score: companies, fsa, company, consumers, banking, banks, bank
## Topic 15 Top Words:
## Highest Prob: young, people, health, mental, youth, prison, drug
## FREX: prisons, probation, cannabis, reoffending, mental, self-harm, drug
## Lift: 0.48, 1-but, 1,000-and, 1,000-such, 1,054,000, 1,099, 1,145
## Score: young, mental, prison, drug, drugs, youth, health
## Topic 16 Top Words:
## Highest Prob: jobs, businesses, business, investment, economy, industry, energy
## FREX: manufacturing, renewable, renewables, solar, low-carbon, carbon, onshore
## Lift: #12.5, #140,000, #23, #25, 0.49, 0.83, 1-are
## Score: energy, jobs, businesses, manufacturing, economy, investment, industry
## Topic 17 Top Words:
## Highest Prob: local, authorities, funding, areas, council, services, authority
## FREX: local, authorities, councils, funding, authority, formula, grant
## Lift: #12,000, #14, #148, #225, #3.6, #4.9, #5,000
## Score: local, authorities, funding, councils, council, authority, services
## Topic 18 Top Words:
## Highest Prob: people, want, one, can, get, say, know
## FREX: things, think, say, something, want, going, get
## Lift: gamu, hailers, intricately, monoglots, unwillingly, 1,027, 1234
## Score: people, get, think, want, things, going, say
## Topic 19 Top Words:
## Highest Prob: children, schools, education, school, child, parents, teachers
## FREX: teachers, pupils, curriculum, sen, academies, ofsted, pupil
## Lift: 14-19, 949,000, academised, as-levels, asperger, authorities-not, authority-maintained
## Score: schools, children, school, education, child, parents, teachers
## Topic 20 Top Words:
## Highest Prob: transport, rail, bus, london, road, travel, line
## FREX: rail, bus, passengers, trains, buses, passenger, airports
## Lift: a49, caa, firstbus, m6, multi-operator, nifca, railways
## Score: rail, transport, bus, passengers, fares, trains, congestion
## Topic 21 Top Words:
## Highest Prob: housing, homes, london, private, people, home, social
## FREX: housing, properties, tenants, landlords, rented, homelessness, homeless
## Lift: 1,113, 1,624, 45.6, 47e, 88.85, 99-year, a24
## Score: housing, homes, tenants, rented, rent, landlords, properties
## Topic 22 Top Words:
## Highest Prob: tax, year, million, budget, increase, billion, cut
## FREX: vat, obr, millionaires, 50p, deficit, budget, tax
## Lift: 0.38, 1,869, 107,500, 13,600, 137.50, 2,073, 2.57

```

```

##      Score: tax, budget, cuts, poverty, billion, chancellor, unemployment
## Topic 23 Top Words:
##      Highest Prob: police, crime, officers, behaviour, policing, home, people
##      FREX: policing, constable, gangs, dubs, tobacco, pcsos, crime
##      Lift: 1.24, adz, anelka, asbos, barchetti, beverages, constable
##      Score: police, crime, officers, policing, antisocial, smoking, behaviour
## Topic 24 Top Words:
##      Highest Prob: bbc, sport, media, culture, football, arts, club
##      FREX: bbc, sports, radio, games, olympic, gambling, bbc's
##      Lift: asentewa, bacta, bandwidth, barbering, benidorm, betting, bluecoat
##      Score: sport, bbc, arts, football, tickets, sports, clubs
## Topic 25 Top Words:
##      Highest Prob: children, child, violence, victims, domestic, abuse, family
##      FREX: abortion, csa, same-sex, rape, adoptive, adopters, barring
##      Lift: same-sex, 0.025, 1,000-discriminates, 1,046, 1,483, 1,746, 10-month-old
##      Score: violence, children, child, sexual, rape, victims, abuse
## Topic 26 Top Words:
##      Highest Prob: planning, land, development, site, water, plymouth, sites
##      FREX: forestry, gypsies, habitats, gypsy, memorials, marine, woodland
##      Lift: 1791, 45-day, addingham, aesthetic, archaeological, archival, bee-friendly
##      Score: land, marine, site, plymouth, sites, planning, museum
## Topic 27 Top Words:
##      Highest Prob: secretary, state, house, last, statement, given, answer
##      FREX: secretary, statement, answer, confirm, state, reply, official
##      Lift: 1-2mc, ashleys, burne, cokey, concentrix's, cover-up, dhar
##      Score: secretary, state, statement, leader, house, answer, confirm
## Topic 28 Top Words:
##      Highest Prob: parliament, wales, scotland, vote, scottish, political, northern
##      FREX: scottish, electoral, polling, voting, ireland, vote, scotland
##      Lift: federalists, gentry, house16, randomisation, calman, voter, @leamingtonsb
##      Score: scottish, vote, electoral, scotland, referendum, wales, elections
## Topic 29 Top Words:
##      Highest Prob: scheme, pension, credit, people, energy, pensions, pensioners
##      FREX: pension, payday, pensioners, prepayment, retirement, savings, debt
##      Lift: 1,105, 1,345, 123,000, 2046, 840,000, aps, boakye
##      Score: pension, pensioners, energy, credit, pensions, fuel, debt
## Topic 30 Top Words:
##      Highest Prob: access, research, data, information, students, university, technology
##      FREX: broadband, data, electronic, student, internet, online, universities
##      Lift: csps, gmail, green-collar, loans-based, msc, remissions, super-fast
##      Score: students, data, university, universities, fees, internet, online

```

4.2.3 Full topic model estimate summary - K30

```

##
## Call:
## estimateEffect(formula = 1:30 ~ short_list, stmobj = topic_model_k30,
##      metadata = lab_corpus_fem_stm$meta, uncertainty = "Global")
##
##
## Topic 1:
##
## Coefficients:

```

```

##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0458830  0.0006737  68.103 <0.0000000000000002 ***
## short_listTRUE -0.0075276  0.0008316  -9.052 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 2:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0649529  0.0005427 119.69 <0.0000000000000002 ***
## short_listTRUE -0.0140242  0.0006184  -22.68 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0399449  0.0005175  77.195 <0.0000000000000002 ***
## short_listTRUE 0.0062665  0.0006560   9.552 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0221290  0.0005940  37.26 <0.0000000000000002 ***
## short_listTRUE 0.0006076  0.0006982   0.87          0.384
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 5:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0713469  0.0005469 130.46 <0.0000000000000002 ***
## short_listTRUE -0.0196329  0.0006401  -30.67 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 6:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0459984  0.0008953  51.379 < 0.0000000000000002 ***
## short_listTRUE -0.0041524  0.0011125  -3.732          0.00019 ***
## ---

```

```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0268220  0.0005620   47.73 <0.0000000000000002 ***
## short_listTRUE 0.0121386  0.0007564   16.05 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 8:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0142025  0.0004701   30.210 <0.0000000000000002 ***
## short_listTRUE 0.0060315  0.0006126    9.846 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 9:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0364720  0.0006392   57.06 <0.0000000000000002 ***
## short_listTRUE -0.0116373  0.0007499  -15.52 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0435502  0.0007363   59.15 <0.0000000000000002 ***
## short_listTRUE -0.0103355  0.0009210  -11.22 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0318529  0.0004394   72.49 < 0.0000000000000002 ***
## short_listTRUE 0.0036461  0.0005861    6.22    0.000000000498 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 12:

```

```

##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0224554  0.0005076   44.24 <0.0000000000000002 ***
## short_listTRUE 0.0080692  0.0006383   12.64 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.02292730  0.00050081   45.78 <0.0000000000000002 ***
## short_listTRUE -0.00002426  0.00060356   -0.04      0.968
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0262849  0.0005358   49.062 < 0.0000000000000002 ***
## short_listTRUE -0.0039614  0.0006532   -6.065      0.00000000133 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0229449  0.0005656   40.569 < 0.0000000000000002 ***
## short_listTRUE -0.0027503  0.0006868   -4.005      0.0000622 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 16:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0358339  0.0007128   50.275 <0.0000000000000002 ***
## short_listTRUE -0.0005323  0.0009207   -0.578      0.563
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 17:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0398844  0.0005018   79.49 <0.0000000000000002 ***

```

```

## short_listTRUE -0.0089579  0.0006040  -14.83 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0846574  0.0005540 152.805 <0.0000000000000002 ***
## short_listTRUE 0.0003664  0.0007016   0.522      0.601
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 19:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0282618  0.0007053  40.071 < 0.0000000000000002 ***
## short_listTRUE 0.0038499  0.0008292   4.643      0.00000344 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0228166  0.0005981  38.149 < 0.0000000000000002 ***
## short_listTRUE 0.0049536  0.0007867   6.297      0.00000000305 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0202281  0.0005996  33.734 < 0.0000000000000002 ***
## short_listTRUE 0.0037261  0.0007081   5.262      0.000000143 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 22:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0440607  0.0008172  53.92 <0.0000000000000002 ***
## short_listTRUE 0.0126824  0.0010481  12.10 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

```



```

##
## Topic 23:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0300320   0.0005983   50.196 <0.0000000000000002 ***
## short_listTRUE -0.0070593   0.0007813   -9.036 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0112160   0.0004463   25.132 <0.0000000000000002 ***
## short_listTRUE 0.0049929   0.0005076    9.836 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 25:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0258047   0.0006243   41.333 < 0.0000000000000002 ***
## short_listTRUE -0.0035748   0.0008062   -4.434    0.00000925 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0145382   0.0004333   33.554 < 0.0000000000000002 ***
## short_listTRUE 0.0022688   0.0005664    4.005    0.000062 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0419219   0.0005333   78.60 <0.0000000000000002 ***
## short_listTRUE 0.0151675   0.0006875   22.06 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 28:
##
## Coefficients:

```

```

##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0228827  0.0005286  43.291 < 0.0000000000000002 ***
## short_listTRUE 0.0055343  0.0006750   8.198 0.00000000000000247 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0265421  0.0005778  45.935 <0.0000000000000002 ***
## short_listTRUE 0.0017457  0.0007249   2.408          0.016 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 30:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0135780  0.0003339  40.663 < 0.0000000000000002 ***
## short_listTRUE 0.0020758  0.0004265   4.868          0.00000113 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

4.3 K60

4.3.1 Shortlists vs Non-Shortlists - K60

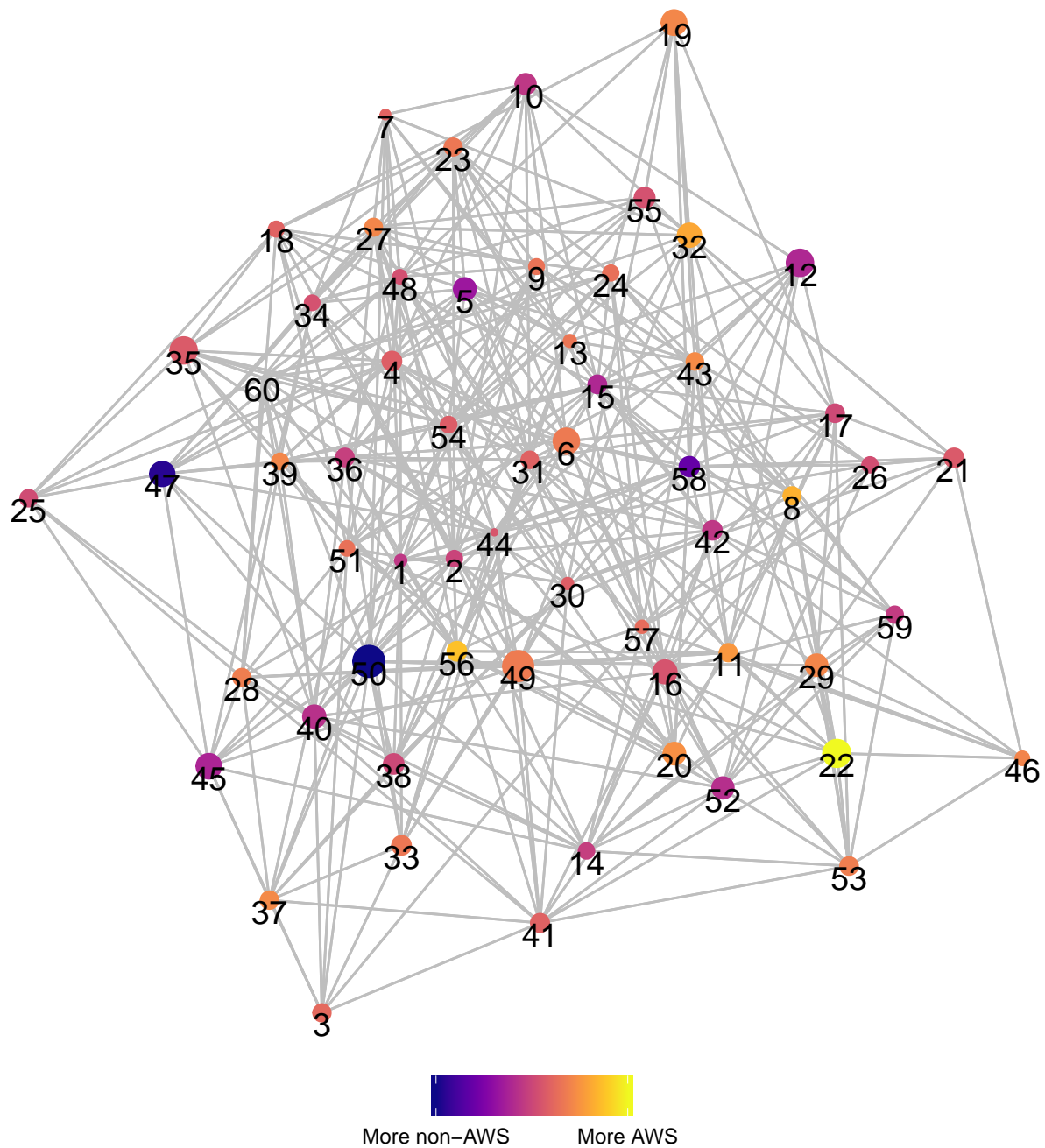


Figure 16: Fruchterman-Reingold plot of K60 Network

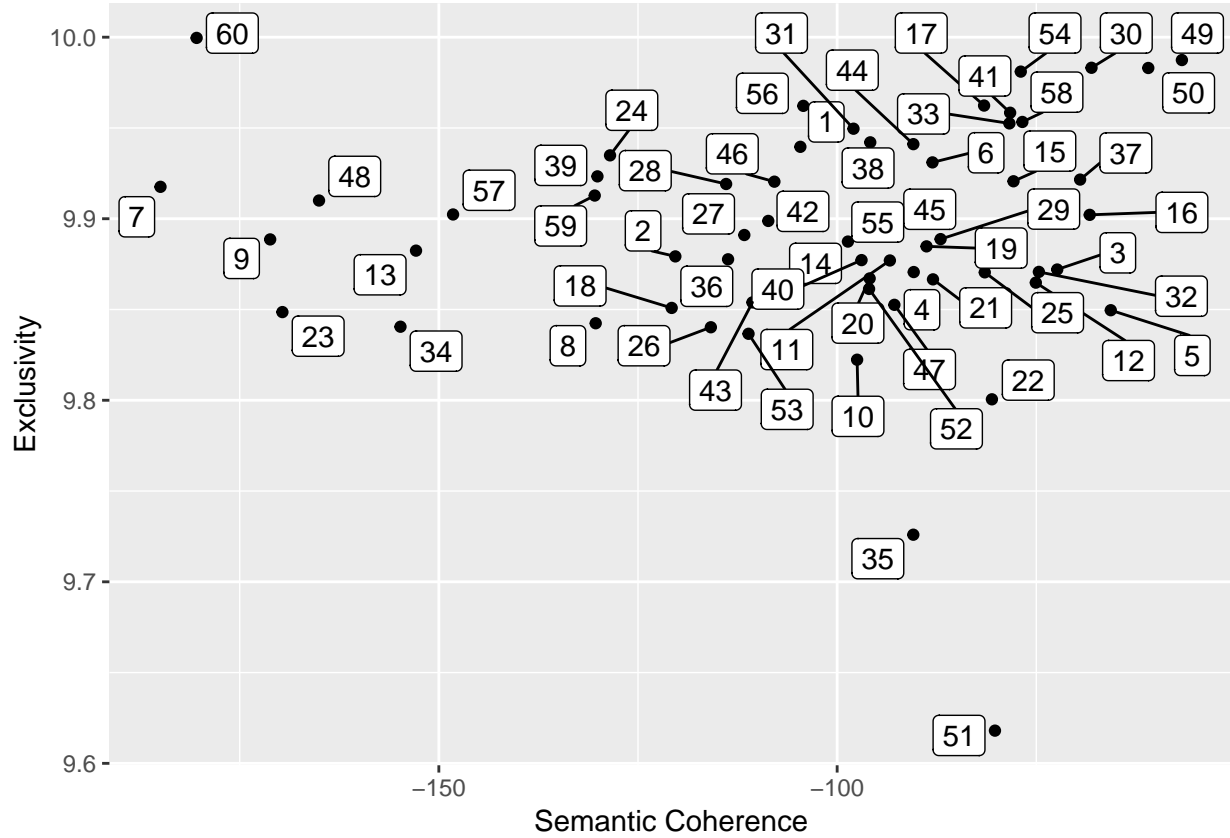


Figure 17: Coherence of K60 Topic Models

Table 17: Count and Distribution of Topics – K60

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
Topic 1	184	0.34%	150	0.54%	540	0.32%
Topic 2	543	1.01%	210	0.75%	1,526	0.9%
Topic 3	689	1.28%	341	1.22%	3,046	1.8%
Topic 4	821	1.53%	447	1.6%	301	0.18%
Topic 5	1,122	2.09%	796	2.86%	3,005	1.77%
Topic 6	2,029	3.77%	786	2.82%	4,255	2.51%
Topic 7	168	0.31%	60	0.22%	175	0.1%
Topic 8	837	1.56%	143	0.51%	1,734	1.02%
Topic 9	501	0.93%	183	0.66%	1,630	0.96%
Topic 10	890	1.65%	656	2.35%	1,418	0.84%
Topic 11	752	1.4%	264	0.95%	1,575	0.93%
Topic 12	1,905	3.54%	1,212	4.35%	4,343	2.56%
Topic 13	307	0.57%	91	0.33%	534	0.32%
Topic 14	432	0.8%	328	1.18%	1,389	0.82%
Topic 15	660	1.23%	440	1.58%	2,102	1.24%
Topic 16	1,434	2.67%	790	2.84%	5,056	2.99%
Topic 17	677	1.26%	405	1.45%	2,867	1.69%

Table 17: Count and Distribution of Topics – K60 (*continued*)

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
Topic 18	484	0.9%	227	0.81%	904	0.53%
Topic 19	1,872	3.48%	773	2.77%	5,577	3.29%
Topic 20	1,391	2.59%	498	1.79%	3,654	2.16%
Topic 21	839	1.56%	449	1.61%	1,385	0.82%
Topic 22	2,584	4.8%	748	2.68%	6,015	3.55%
Topic 23	724	1.35%	282	1.01%	1,434	0.85%
Topic 24	523	0.97%	198	0.71%	1,541	0.91%
Topic 25	554	1.03%	363	1.3%	995	0.59%
Topic 26	483	0.9%	257	0.92%	1,218	0.72%
Topic 27	709	1.32%	276	0.99%	1,627	0.96%
Topic 28	777	1.44%	252	0.9%	3,762	2.22%
Topic 29	1,333	2.48%	514	1.84%	2,903	1.71%
Topic 30	232	0.43%	96	0.34%	882	0.52%
Topic 31	594	1.1%	328	1.18%	1,973	1.17%
Topic 32	1,719	3.2%	538	1.93%	2,452	1.45%
Topic 33	962	1.79%	305	1.09%	3,373	1.99%
Topic 34	434	0.81%	232	0.83%	1,179	0.7%
Topic 35	2,021	3.76%	1,072	3.85%	9,682	5.72%
Topic 36	702	1.31%	396	1.42%	1,632	0.96%
Topic 37	817	1.52%	236	0.85%	2,673	1.58%
Topic 38	961	1.79%	485	1.74%	3,719	2.2%
Topic 39	616	1.15%	194	0.7%	1,111	0.66%
Topic 40	1,213	2.26%	806	2.89%	6,070	3.58%
Topic 41	743	1.38%	414	1.49%	3,874	2.29%
Topic 42	699	1.3%	545	1.96%	1,588	0.94%
Topic 43	685	1.27%	215	0.77%	1,466	0.87%
Topic 44	105	0.2%	36	0.13%	100	0.06%
Topic 45	1,572	2.92%	1,029	3.69%	7,673	4.53%
Topic 46	449	0.83%	96	0.34%	522	0.31%
Topic 47	1,183	2.2%	1,352	4.85%	4,523	2.67%
Topic 48	322	0.6%	222	0.8%	409	0.24%
Topic 49	3,174	5.9%	1,095	3.93%	16,081	9.5%
Topic 50	2,284	4.25%	2,364	8.48%	14,030	8.29%
Topic 51	448	0.83%	196	0.7%	1,798	1.06%
Topic 52	1,003	1.86%	796	2.86%	4,085	2.41%
Topic 53	782	1.45%	304	1.09%	1,819	1.07%
Topic 54	547	1.02%	240	0.86%	1,516	0.9%
Topic 55	895	1.66%	595	2.14%	1,063	0.63%
Topic 56	1,001	1.86%	265	0.95%	2,685	1.59%
Topic 57	273	0.51%	138	0.5%	587	0.35%
Topic 58	669	1.24%	723	2.59%	2,569	1.52%
Topic 59	459	0.85%	411	1.48%	1,696	1%

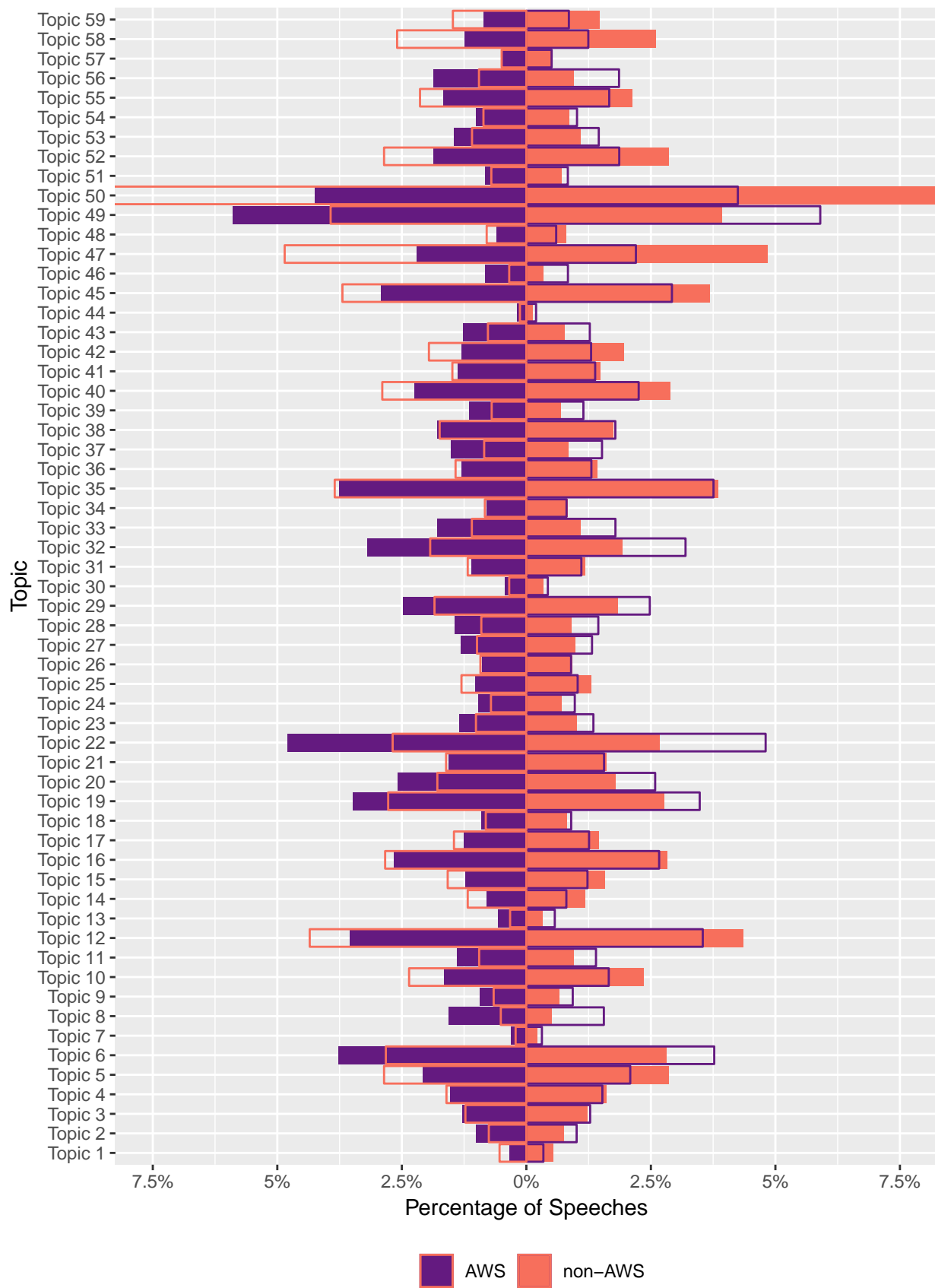


Figure 18: K60 Pyramid Chart

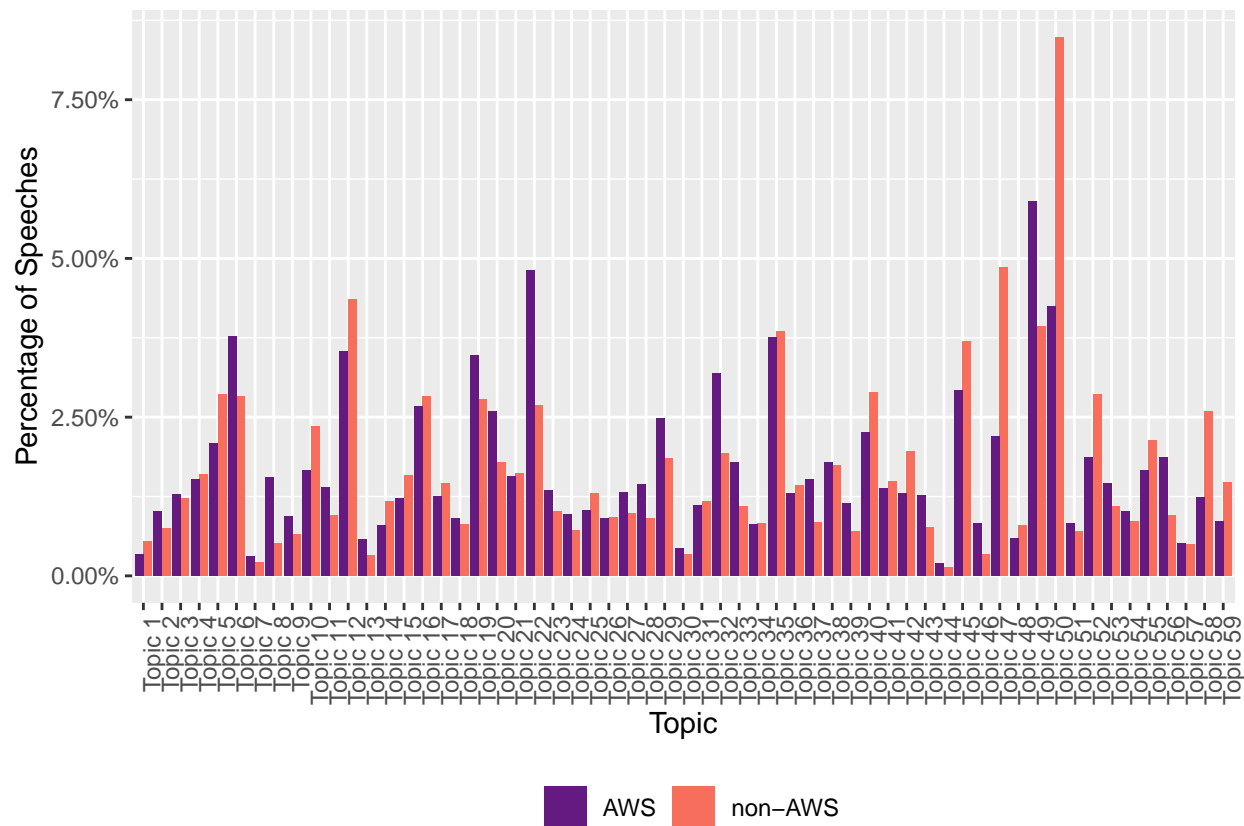


Figure 19: K60 Bar Chart

4.3.1.1 Word Occurences

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

Table 18: Words in topic - K60

Topic Number	Top Ten Words	Top Ten FREX
Topic 1	information, practice, guidance, data, available, advice, use, service, code, complaints, technology, website, ensure, provided, commissioner, records, details, also, internet, communication	code, information, data, ombudsman, practice, complaints, electronic, guidance, communications, website, requests, communication, records, sharing, dissent, assent, accurate, codes, advisers, privacy
Topic 2	safety, regulation, standards, regulations, industry, health, air, indicated, risk, use, regulatory, enforcement, licensing, directive, environmental, licence, noise, aviation, also, legislation	hse, caa, indicated, sunbeds, sunbed, fireworks, noise, aviation, herbal, safety, medicines, airlines, airports, directive, regulation, gatwick, asbestos, air, supplements, co-proxamol

Table 18: Words in topic - K60 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 3	member, members, said, made, north, heard, spoke, also, debate, friends, speech, south, east, mentioned, talked, raised, west, pointed, many, comments	member, thoughtful, spoke, eastmr, hayes, eloquently, southmr, westmr, redwood, bermondsey, northmr, talked, holborn, wokinghammr, rushcliffemr, durhammr, norfolkmr, harlingtonjohn, valleymr, dorsetmr
Topic 4	women, violence, men, domestic, women's, pay, woman, work, girls, equal, gender, gap, female, equality, sexual, male, many, maternity, still, victims	women, fgm, women's, shortlists, men, male, female, violence, girls, domestic, gender, paternity, woman, refuges, men's, maternity, all-women, pregnant, sanitary, refuge
Topic 5	police, crime, officers, behaviour, policing, antisocial, home, community, people, tackle, force, forces, powers, communities, serious, neighbourhood, chief, streets, officer, support	policing, antisocial, police, crime, officers, pcsos, behaviour, constable, graffiti, asbos, soca, neighbourhood, gang, constabulary, knife, cctv, constables, gangs, burglary, wardens
Topic 6	made, make, department, progress, taking, recent, ensure, action, assessment, impact, government, steps, statement, discussions, plans, strategy, development, northern, commitment, measures	progress, steps, discussions, assessment, taking, department, recent, strategy, northern, representations, developing, action, plans, statement, department's, ireland, implementation, priority, targets, departmental
Topic 7	hearing, touch, aids, people, hiv, database, dna, blind, deaf, can, also, copyright, loss, helpline, reemploy, national, impaired, epilepsy, use, however	deaf, reemploy, epilepsy, b12, aids, impaired, copyright, hiv, hearing, blind, hpa, dna, touch, database, rnib, visually, helpline, impairment, fortification, nerve
Topic 8	food, water, rural, flood, farmers, environment, flooding, products, risk, people, affairs, meat, floods, agency, agricultural, country, waste, industry, eat, agriculture	flood, flooding, beef, dairy, meat, ofwat, food, floods, water, cocoa, trussell, defences, labelling, fruit, sugar, eat, farmers, agriculture, flooded, gm
Topic 9	animals, marine, dogs, animal, fishing, dog, sea, welfare, fish, industry, ban, fisheries, wildlife, environment, conservation, also, many, fishermen, morecambe, species	fishing, fishermen, species, fur, cod, mink, circuses, snares, rspca, seafarers, mmo, animals, peat, fish, marine, dog, cfp, puppies, animal, fisheries
Topic 10	health, mental, treatment, cancer, medical, disease, patients, can, condition, national, people, screening, conditions, problems, heart, also, clinical, group, research, diagnosis	cancer, flu, prostate, cervical, cancers, endometriosis, piercing, mental, screening, immunisation, stroke, breast, diagnosis, mrsa, diagnosed, symptoms, diabetes, infection, infections, disease
Topic 11	cuts, cut, council, government, liberal, local, hull, city, councils, services, public, democrats, tories, budget, country, tory, budgets, areas, coalition, democrat	lib, liberal, tories, cuts, hull, democrats, democrat, pledge, cut, dem, budgets, tory, scrapped, cutting, dems, scrapping, scrap, coalition, slashed, lewisham

Table 18: Words in topic - K60 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 12	care, health, nhs, services, hospital, patients, service, social, trust, hospitals, staff, trusts, patient, need, primary, people, nurses, waiting, community, e	helier, hospitals, pct, nhs, hospital, trusts, e, nursing, commissioning, dementia, beds, gp, acute, pharmacies, patients, nurses, pcts, patient, midwives, in-patient
Topic 13	emergency, fire, service, phone, mobile, calls, john, ambulance, rescue, sir, public, incident, call, incidents, services, phones, blood, ms, lives, firefighters	firefighters, fire, phones, cpr, mobile, phone, rescue, ambulance, masts, fires, coastguard, emergency, ms, ambulances, john, crews, paramedics, emergencies, gannet, clyde
Topic 14	companies, company, tax, competition, financial, market, consumers, uk, industry, regime, rules, fair, business, public, fsa, services, regulatory, transparency, profits, trading	fsa, competition, hmrc, corporate, policyholders, liabilities, shares, avoidance, shareholders, dependencies, evasion, penrose, regulators, liability, company's, companies, oft, company, equitable, directors
Topic 15	community, organisations, work, role, services, voluntary, support, public, social, groups, sector, important, programme, working, service, together, play, good, society, project	voluntary, organisations, bbc, programmes, role, play, project, organisation, exclusion, innovative, radio, groups, community, initiatives, volunteers, volunteering, bristol, ideas, develop, charter
Topic 16	jobs, economy, economic, investment, growth, industry, regional, future, new, development, need, skills, uk, manufacturing, country, sector, world, north-east, infrastructure, region	manufacturing, steel, economy, growth, regional, economic, jobs, productivity, economies, north-east, prosperity, regions, industries, inward, recession, region, construction, investment, downturn, invest
Topic 17	million, funding, money, increase, billion, extra, year, additional, fund, spending, cost, costs, investment, resources, budget, spent, 1, new, funds, next	funding, million, expenditure, formula, extra, billion, grant, spent, fund, allocated, money, spending, funds, additional, funded, spend, invested, allocation, plymouth, 2007-08
Topic 18	communities, black, language, minority, community, church, ethnic, faith, people, country, religious, english, many, groups, forced, prevent, muslim, marriage, freedom, hate	sikh, hatred, muslim, humanist, holocaust, islam, ethnic, extremism, church, racism, asian, black, hate, religious, muslims, faith, faiths, priests, minority, minorities
Topic 19	education, schools, school, children, teachers, students, skills, pupils, educational, learning, special, parents, college, primary, needs, university, training, good, standards, higher	teachers, pupils, curriculum, sen, academies, ofsted, pupil, grammar, schools, fe, gcse, school, education, teaching, post-16, educational, teacher, students, academy, attainment
Topic 20	transport, rail, bus, services, line, travel, network, train, passengers, london, fares, service, public, capacity, trains, new, road, main, manchester, railway	rail, bus, fares, buses, hs2, freight, high-speed, electrification, crossrail, franchising, railtrack, passengers, apd, transport, trains, railways, passenger, congestion, commuter, fare

Table 18: Words in topic - K60 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 21	housing, homes, social, affordable, need, accommodation, home, people, new, council, building, homelessness, families, build, benefit, live, homeless, built, buy, houses	homelessness, housing, homeless, accommodation, homes, affordable, associations, rough, sleeping, starter, first-time, empty, decent, hamlets, houses, sleepers, overcrowded, stock, 106, ladder
Topic 22	tax, chancellor, poverty, budget, families, pay, rate, wage, living, working, income, year, cut, increase, impact, minimum, people, credits, benefit, vat	obr, millionaires, 50p, vat, wage, credits, chancellor, tax, inflation, fiscal, chancellor's, wages, deficit, forecast, incomes, exchequer, earning, poverty, taxes, richest
Topic 23	alcohol, smoking, people, ban, tobacco, online, israel, advertising, young, drinking, public, palestinian, israeli, pubs, gaza, internet, cull, smoke, images, tb	tobacco, palestinian, israeli, gaza, palestinians, hamas, israelis, culls, israel's, israel, two-state, cull, smoking, tb, alcohol, pornography, images, drinking, badger, badgers
Topic 24	culture, sport, media, football, clubs, arts, club, sports, creative, games, lottery, music, cultural, olympics, swimming, facilities, olympic, events, many, event	sport, games, olympic, gambling, lap-dancing, olympics, arts, casinos, creative, swimming, music, sports, football, club, sporting, venues, lottery, gaming, lincoln, rugby
Topic 25	rights, human, law, act, equality, discrimination, legislation, bill, civil, commission, society, convention, marriage, legal, protection, couples, duty, age, equal, respect	csa, same-sex, rights, discrimination, gay, abortion, couples, lesbian, human, equality, married, ehrc, abortions, lgbt, discriminated, sexuality, convention, law, heterosexual, discriminate
Topic 26	planning, development, land, sites, site, building, new, green, buildings, national, infrastructure, use, environment, urban, forest, application, policy, developments, heritage, permission	gypsies, gypsy, planning, sites, museum, nppf, forest, brownfield, site, belt, stevenage, open-cast, forestry, spaces, travellers, heritage, buildings, land, parks, dean
Topic 27	family, constituent, families, case, death, inquiry, happened, told, man, died, lost, home, many, never, victims, justice, life, mrs, received, day	inquest, bereaved, constituent, mrs, died, son, hillsborough, survivors, daughter, tragedy, husband, death, contacted, inquiry, loved, tragic, coroner, happened, wife, primodos
Topic 28	vote, political, election, people, parties, elected, party, democracy, elections, electoral, register, voting, parliament, general, politics, voted, system, registration, democratic, one	electoral, vote, voting, elections, votes, democracy, polling, voter, political, ballot, voters, elected, turnout, voted, electorate, democratic, election, parties, candidate, candidates
Topic 29	scheme, pension, pensions, benefit, pensioners, credit, system, income, benefits, insurance, payments, savings, schemes, payment, age, people, universal, retirement, changes, paid	pension, annuity, pensions, pensioners, retirement, annuities, pensioner, payment, insurance, payments, entitlement, take-up, scheme, qualify, savings, saving, income, earnings, universal, eligible

Table 18: Words in topic - K60 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 30	years, time, now, two, one, first, three, past, week, months, last, ago, 10, five, still, next, every, four, times, long	months, years, three, two, ago, past, five, time, four, weeks, week, now, 10, six, days, hours, times, half, first, long
Topic 31	year, number, since, last, report, figures, said, show, official, april, march, 2010, figure, published, increase, end, 1997, increased, january, month	official, march, january, figures, april, june, since, 2011, november, july, september, december, figure, vol, october, year, 1997, february, 2008, 2010
Topic 32	people, work, young, support, disabled, carers, help, employment, get, many, benefit, need, youth, disability, benefits, older, job, allowance, person, social	disabled, carers, dla, incapacity, disabilities, jobcentre, esa, caring, young, unemployed, jobcentres, youth, disability, jsa, pip, older, apprenticeships, atos, jobseeker's, carer
Topic 33	question, order, asked, mr, answer, questions, speaker, put, deputy, point, ask, written, agreed, made, may, read, minutes, letter, correct, call	answer, question, questions, speaker, mr, order, deputy, asked, apologise, forthwith, answers, madam, write, written, answered, correct, minutes, o'clock, asking, advise
Topic 34	drugs, drug, road, charities, people, car, vehicles, charity, use, driving, vehicle, drivers, cars, problem, driver, can, cannabis, also, parking, misuse	crb, cannabis, bikes, barring, motor, taxi, drivers, vehicles, driver, gift, vehicle, supervised, parking, substances, barred, drugs, drug, mph, donations, charities
Topic 35	international, defence, forces, world, armed, countries, foreign, security, war, british, un, conflict, military, aid, us, support, country, uk, afghanistan, must	iraq, syria, troops, nato, sierra, zimbabwe, syrian, burma, iraqi, leone, yemen, daesh, afghan, genocide, ceasefire, congo, burmese, assad, taliban, libya
Topic 36	home, office, immigration, uk, security, country, system, asylum, people, british, fraud, identity, applications, rules, citizens, border, foreign, migration, checks, passport	immigration, asylum, passport, passports, seekers, migration, nationals, identity, fraud, cards, border, id, points-based, nationality, appeals, migrants, deported, biometric, visa, visas
Topic 37	house, members, debate, time, today, parliament, leader, opportunity, us, committee, chamber, motion, speak, place, debates, business, sides, many, issue, parliamentary	house, debates, leader, debate, backbench, chamber, sides, debating, members, debated, motion, tonight, recess, session, tomorrow, cross-party, commons, lobby, back-bench, sitting
Topic 38	committee, report, public, review, independent, commission, select, work, evidence, recommendations, process, set, scrutiny, system, role, board, audit, also, national, government	select, recommendations, committees, audit, scrutiny, committee's, independent, review, committee, recommendation, report, accountability, reviews, panel, appointed, chairman, reports, appointments, conclusions, oversight

Table 18: Words in topic - K60 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 39	wales, prison, welsh, assembly, england, prisoners, cardiff, prisons, offenders, justice, probation, service, commissioner, swansea, newport, custody, devolution, devolved, sentences, bridgend	wales, welsh, prisons, cymru, assembly, prison, prisoners, s4c, reoffending, prisoner, probation, hmp, cardiff, newport, neath, bridgend, swansea, llanwern, llanelli, custody
Topic 40	european, eu, scotland, scottish, uk, union, europe, united, countries, states, trade, parliament, kingdom, agreement, negotiations, treaty, british, national, council, referendum	scottish, lisbon, scotland, eu, european, brexit, treaty, wto, europe, gibraltar, snp, holyrood, negotiations, membership, enlargement, scotland's, accession, union, euro, scots
Topic 41	government, labour, conservative, government's, policy, opposition, party, back, previous, us, country, nothing, let, said, speech, support, conservatives, now, failed, proposals	conservative, conservatives, opposition, labour, government, benches, failed, previous, party, nothing, queen's, policy, party's, opposed, promises, abolish, back, government's, rhetoric, interruption
Topic 42	staff, workers, work, training, employers, pay, working, service, contracts, contract, job, new, employment, employees, force, unions, doctors, trade, recruitment, dentists	dentists, dental, dentistry, employers, contract, contracts, workers, posts, concentrix, junior, employer, employees, recruitment, employee, zero-hours, recruit, dentist, employed, contractors, redundancies
Topic 43	constituency, council, area, centre, residents, west, north, local, county, petition, constituents, town, south, yorkshire, city, closure, east, borough, close, petitioners	petitioners, declares, petition, immingham, swindon, county, lincolnshire, durham, lancashire, warrington, hackney, essex, yorkshire, derbyshire, halifax, humber, wakefield, closure, residents, urges
Topic 44	making, access, decision, decisions, make, made, interests, lack, best, without, case, open, taken, powerful, criteria, capacity, clear, digital, ability, delay	broadband, decisions, decision, making, access, criteria, powerful, interests, crawley, advocacy, decision-making, superfast, digital, lack, delay, firmly, cdc, roll-out, easier, healthwatch
Topic 45	bill, clause, amendment, new, amendments, legislation, act, provisions, committee, lords, powers, section, power, 1, provision, clauses, may, made, regulations, 2	clause, amendment, amendments, nos, insert, clauses, provisions, lords, bill, bill's, schedule, tabled, section, page, passage, definition, beg, amend, amended, drafted
Topic 46	private, sector, public, tenants, landlords, property, rent, bedroom, move, properties, many, rented, pay, cap, nottingham, affected, letting, rents, room, impact	private, hmos, landlords, bedroom, tenants, letting, privately, tenancy, discretionary, rented, sector, arrears, tenancies, tenant, rent, nottingham, eviction, spare, landlord, rents
Topic 47	cases, court, legal, justice, case, criminal, law, courts, evidence, offence, victims, offences, prosecution, system, orders, serious, rape, person, can, whether	cps, defendants, defendant, tpims, courts, court, attorney-general, judicial, prosecution, magistrates, extradition, sfo, offence, warrant, judges, conviction, judge, prosecutions, tpim, offences

Table 18: Words in topic - K60 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 48	research, science, trafficking, human, engineering, technology, stem, slough, university, slavery, census, universities, scientific, uk, cell, cells, trafficked, statistics, exploitation, embryos	stem, embryonic, slavery, embryos, fss, science, census, trafficked, cloning, slough, trafficking, research, ons, prostitution, embryo, slave, fertilisation, cell, engineering, hfea
Topic 49	people, want, get, one, say, think, know, us, go, see, going, just, said, much, make, like, can, things, good, many	think, things, say, something, going, get, want, lot, saying, go, really, thing, talking, talk, quite, trying, thought, bit, got, idea
Topic 50	important, issue, point, take, need, issues, however, consider, whether, can, possible, must, matter, deal, understand, also, place, course, different, hope	important, issues, consider, point, issue, possible, understand, makes, matter, certainly, raised, points, extremely, different, course, lady, gentleman's, shall, considering, take
Topic 51	constituency, people, proud, many, labour, great, speech, one, first, new, world, also, years, life, history, maiden, city, parliament, member, like	maiden, famous, queen, pride, miners, proud, memorial, anniversary, honour, thatcher, jo, fusiliers, predecessor, rochdale, predecessors, mp, gracious, lothian, nelson, battalion
Topic 52	energy, fuel, climate, change, prices, green, gas, companies, carbon, bills, power, market, price, emissions, oil, efficiency, electricity, new, winter, wind	electricity, renewables, solar, ofgem, feed-in, energy, tariffs, fuel, carbon, renewable, climate, gas, oil, emissions, dioxide, generators, kyoto, tariff, wind, co2
Topic 53	bank, debt, financial, banks, credit, advice, fees, people, interest, pay, money, banking, loan, loans, lending, levy, payday, cost, many, citizens	loan, lending, payday, bureaux, loans, farepak, debt, bank, fees, debts, lenders, banking, banks, rbs, rock, fca, bankers, borrowers, imf, high-cost
Topic 54	can, welcome, sure, aware, may, many, work, thank, constituents, support, particularly, hope, ensure, constituency, concern, done, great, pleased, especially, grateful	welcome, aware, sure, thank, friend's, discuss, pleased, assure, concern, attention, grateful, particularly, especially, constituents, giving, reply, share, done, join, delighted
Topic 55	children, child, care, parents, families, family, children's, support, vulnerable, abuse, parent, social, need, many, help, start, home, adoption, working, needs	child, adopters, children's, children, parent, adoption, child's, parents, dubs, lone, looked-after, cafcass, parental, adoptive, mothers, grandparents, foster, nursery, nurseries, placement
Topic 56	secretary, state, ministers, tell, whether, said, statement, confirm, today, explain, minister's, us, can, now, yesterday, ask, yet, says, announcement, response	secretary, state, confirm, state's, tell, minister's, ministers, explain, please, announcement, yesterday, urgent, assurances, clarify, press, statement, under-secretary, cabinet, talks, expects
Topic 57	london, mayor, property, estate, market, value, tickets, charge, sale, westminster, charges, sold, duty, stamp, boroughs, buy, london's, ticket, selling, land	leaseholders, leasehold, leases, touts, freehold, londoners, boroughs, london, london's, kensington, stamp, lease, tickets, mayor, seller, chelsea, estate, leaseholder, redbridge, ticket

Table 18: Words in topic - K60 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 58	local, authorities, authority, areas, area, consultation, services, proposals, new, needs, communities, government, councils, ensure, provision, provide, system, level, set, paper	authorities, authority, local, consultation, locally, strategic, councils, areas, proposals, provision, forums, white, stakeholders, partnerships, councillors, paper, area, flexibility, consult, authority's
Topic 59	small, business, businesses, office, post, offices, royal, rates, mail, service, network, rural, services, new, firms, many, shops, waste, large, shop	mail, offices, sub-post, post, businesses, small, medium-sized, sub-postmasters, smes, business, entrepreneurs, enterprises, recycling, branches, consignia, shop, stores, retail, q, postcomm
Topic 60	agree, given, accept, absolutely, totally, unacceptable, surely, mentions, describes, reconsider, entirely, country, describing, fact, across, rather, imperative, take, can, putting	agree, given, accept, absolutely, mentions, totally, describes, unacceptable, surely, reconsider, describing, entirely, imperative, rather, fact, putting, country, completely, across, regret

4.3.2 Full topic model summary - K60

A topic model with 60 topics, 81651 documents and a 119586 word dictionary.

Topic 1 Top Words:

Highest Prob: information, practice, guidance, data, available, advice, use
 ## FREX: code, information, data, ombudsman, practice, complaints, electronic
 ## Lift: @daisydumble, @percyblakeney63, 1-on, 1,200-i, 1.3-that, 108-are, 1082
 ## Score: information, data, code, practice, guidance, complaints, ombudsman

Topic 2 Top Words:

Highest Prob: safety, regulation, standards, regulations, industry, health, air
 ## FREX: hse, caa, indicated, sunbeds, sunbed, fireworks, noise
 ## Lift: aerodromes, aps, aristolochia, atol-protected, caa, calor, cay
 ## Score: safety, regulation, aviation, fireworks, airports, noise, regulations

Topic 3 Top Words:

Highest Prob: member, members, said, made, north, heard, spoke
 ## FREX: member, thoughtful, spoke, eastmr, hayes, eloquently, southmr
 ## Lift: 1028, 12-he, 1270s, 130b, 17-year-olds-those, 1993-more, 2,065
 ## Score: member, north, members, spoke, east, south, speech

Topic 4 Top Words:

Highest Prob: women, violence, men, domestic, women's, pay, woman
 ## FREX: women, fgm, women's, shortlists, men, male, female
 ## Lift: #112, #7, #9, #neverthelesshepersisted, 1-breast-feed, 1,678, 1.57
 ## Score: women, violence, women's, men, girls, gender, domestic

Topic 5 Top Words:

Highest Prob: police, crime, officers, behaviour, policing, antisocial, home
 ## FREX: policing, antisocial, police, crime, officers, pcsos, behaviour
 ## Lift: antisocial, asbos, constabulary, hmic, #22k, #29k, 1-2-3
 ## Score: police, crime, officers, policing, antisocial, behaviour, constable

Topic 6 Top Words:

Highest Prob: made, make, department, progress, taking, recent, ensure

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##      FREX: progress, steps, discussions, assessment, taking, department, recent
##      Lift: cancun, ofa, 1-2ws, 10.42, 101269, 101548, 101549
##      Score: assessment, statement, progress, department, steps, northern, ireland
## Topic 7 Top Words:
##      Highest Prob: hearing, touch, aids, people, hiv, database, dna
##      FREX: deaf, remploy, epilepsy, b12, aids, impaired, copyright
##      Lift: b12, deaf, epilepsy, fortification, #640, 0.01, 1-to-1
##      Score: aids, hearing, hiv, deaf, dna, remploy, database
## Topic 8 Top Words:
##      Highest Prob: food, water, rural, flood, farmers, environment, flooding
##      FREX: flood, flooding, beef, dairy, meat, ofwat, food
##      Lift: 1072, 70-80, 915, abebrese, allergen, at-a-glance, awb's
##      Score: food, water, farmers, flood, flooding, rural, floods
## Topic 9 Top Words:
##      Highest Prob: animals, marine, dogs, animal, fishing, dog, sea
##      FREX: fishing, fishermen, species, fur, cod, mink, circuses
##      Lift: aquaculture, bee-friendly, birdlife, braniff, bull-type, by-catch, bycatch
##      Score: animals, marine, fishing, animal, dogs, fishermen, fisheries
## Topic 10 Top Words:
##      Highest Prob: health, mental, treatment, cancer, medical, disease, patients
##      FREX: cancer, flu, prostate, cervical, cancers, endometriosis, piercing
##      Lift: 1169, 20-fold, ablation, antigen, arrhythmogenic, asymptomatic, bed-occupancy
##      Score: cancer, mental, health, patients, disease, treatment, screening
## Topic 11 Top Words:
##      Highest Prob: cuts, cut, council, government, liberal, local, hull
##      FREX: lib, liberal, tories, cuts, hull, democrats, democrat
##      Lift: lib, 0.2966, 0.37, 0.5524, 1,439, 1,608, 1,814
##      Score: cuts, liberal, hull, cut, democrats, councils, local
## Topic 12 Top Words:
##      Highest Prob: care, health, nhs, services, hospital, patients, service
##      FREX: helier, hospitals, pct, nhs, hospital, trusts, e
##      Lift: 2005-6, acos, admittances, ent, epsom's, farm's, fieldman
##      Score: nhs, care, patients, hospital, health, services, patient
## Topic 13 Top Words:
##      Highest Prob: emergency, fire, service, phone, mobile, calls, john
##      FREX: firefighters, fire, phones, cpr, mobile, phone, rescue
##      Lift: firefighters, #ftvote, #timeforthetruth, 03, 0315, 0345, 070
##      Score: fire, ambulance, emergency, mobile, phone, firefighters, rescue
## Topic 14 Top Words:
##      Highest Prob: companies, company, tax, competition, financial, market, consumers
##      FREX: fsa, competition, hmrc, corporate, policyholders, liabilities, shares
##      Lift: #45, 1,643, 1,699,137, 10-month, 10,000-with, 1174, 12,965.80
##      Score: companies, tax, fsa, company, consumers, competition, hmrc
## Topic 15 Top Words:
##      Highest Prob: community, organisations, work, role, services, voluntary, support
##      FREX: voluntary, organisations, bbc, programmes, role, play, project
##      Lift: cbbc, communitybuilders, connectives, counterfeiter, county-sized, futurebuilders, inter
##      Score: organisations, community, voluntary, bbc, sector, services, programmes
## Topic 16 Top Words:
##      Highest Prob: jobs, economy, economic, investment, growth, industry, regional
##      FREX: manufacturing, steel, economy, growth, regional, economic, jobs
##      Lift: #1,150, #12.5, #140,000, #23, #25, 1,126, 1,443
##      Score: jobs, economy, manufacturing, investment, growth, industry, economic
## Topic 17 Top Words:

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Highest Prob: million, funding, money, increase, billion, extra, year
 ## FREX: funding, million, expenditure, formula, extra, billion, grant
 ## Lift: #3,850, 0.15, 0.41, 000-to, 1,808, 1.245, 1.637
 ## Score: funding, million, money, billion, spending, fund, investment
 ## Topic 18 Top Words:
 ## Highest Prob: communities, black, language, minority, community, church, ethnic
 ## FREX: sikh, hatred, muslim, humanist, holocaust, islam, ethnic
 ## Lift: #356, #38, 1,027, 1,483, 10-46, 100,000-and, 107th
 ## Score: ethnic, religious, muslim, church, holocaust, hatred, marriage
 ## Topic 19 Top Words:
 ## Highest Prob: education, schools, school, children, teachers, students, skills
 ## FREX: teachers, pupils, curriculum, sen, academies, ofsted, pupil
 ## Lift: curriculum, gcses, headteachers, school's, sen, 1,000-pupil, 1,051
 ## Score: schools, school, education, teachers, pupils, students, children
 ## Topic 20 Top Words:
 ## Highest Prob: transport, rail, bus, services, line, travel, network
 ## FREX: rail, bus, fares, buses, hs2, freight, high-speed
 ## Lift: euston, franchising, #145, 0.1p, 0.45, 1-very, 1,658
 ## Score: rail, transport, bus, passengers, fares, trains, hs2
 ## Topic 21 Top Words:
 ## Highest Prob: housing, homes, social, affordable, need, accommodation, home
 ## FREX: homelessness, housing, homeless, accommodation, homes, affordable, associations
 ## Lift: 1,624, bramwell, clearsprings, clts, sleepers, #19, #21.5
 ## Score: housing, homes, affordable, homelessness, accommodation, homeless, rent
 ## Topic 22 Top Words:
 ## Highest Prob: tax, chancellor, poverty, budget, families, pay, rate
 ## FREX: obr, millionaires, 50p, vat, wage, credits, chancellor
 ## Lift: obr, #3.5, #840, 0.38, 0.76p, 1,196, 1,226
 ## Score: tax, wage, poverty, credits, chancellor, budget, vat
 ## Topic 23 Top Words:
 ## Highest Prob: alcohol, smoking, people, ban, tobacco, online, israel
 ## FREX: tobacco, palestinian, israeli, gaza, palestinians, hamas, israelis
 ## Lift: #no2lgbthate, 0.7p, 1,000-almost, 1,010, 1,032, 1,366,082, 1,424
 ## Score: smoking, alcohol, israel, tobacco, palestinian, israeli, gaza
 ## Topic 24 Top Words:
 ## Highest Prob: culture, sport, media, football, clubs, arts, club
 ## FREX: sport, games, olympic, gambling, lap-dancing, olympics, arts
 ## Lift: aquatics, asentewa, athletes, bacta, blatter, bluecoat, casinos
 ## Score: sport, arts, football, sports, clubs, games, olympic
 ## Topic 25 Top Words:
 ## Highest Prob: rights, human, law, act, equality, discrimination, legislation
 ## FREX: csa, same-sex, rights, discrimination, gay, abortion, couples
 ## Lift: 193,000, admixed, bpas, cre, discriminator, drc's, ehrc
 ## Score: rights, human, discrimination, equality, marriage, law, couples
 ## Topic 26 Top Words:
 ## Highest Prob: planning, development, land, sites, site, building, new
 ## FREX: gypsies, gypsy, planning, sites, museum, nppf, forest
 ## Lift: broadfield, gypsies, #tartantories, 1,000-year-old, 10-we, 10,996, 10.20
 ## Score: planning, land, sites, site, development, museum, brownfield
 ## Topic 27 Top Words:
 ## Highest Prob: family, constituent, families, case, death, inquiry, happened
 ## FREX: inquest, bereaved, constituent, mrs, died, son, hillsborough
 ## Lift: 1,454, 10,000-seat, 1004, 113-page, 1141, 124a, 13822
 ## Score: constituent, died, families, death, inquiry, family, inquest


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## Topic 28 Top Words:
##   Highest Prob: vote, political, election, people, parties, elected, party
##   FREX: electoral, vote, voting, elections, votes, democracy, polling
##   Lift: 1-would, 1,333, 1,516,000, 1034, 1053, 121543, 128,000
##   Score: vote, electoral, elections, voting, election, democracy, political
## Topic 29 Top Words:
##   Highest Prob: scheme, pension, pensions, benefit, pensioners, credit, system
##   FREX: pension, annuity, pensions, pensioners, retirement, annuities, pensioner
##   Lift: gwp, annuities, pension, #20,000, #400, 1,000-that, 1,482
##   Score: pension, pensioners, pensions, scheme, insurance, credit, retirement
## Topic 30 Top Words:
##   Highest Prob: years, time, now, two, one, first, three
##   FREX: months, years, three, two, ago, past, five
##   Lift: frazzled, lilian's, non-stipendiary, term-time, 10-week-old, 11-month, 196b
##   Score: years, time, months, hours, week, weeks, ago
## Topic 31 Top Words:
##   Highest Prob: year, number, since, last, report, figures, said
##   FREX: official, march, january, figures, april, june, since
##   Lift: 1-2mc, 601, 1,033, 1,124,818, 1,130, 1,337, 1,367
##   Score: year, figures, official, vol, since, report, last
## Topic 32 Top Words:
##   Highest Prob: people, work, young, support, disabled, carers, help
##   FREX: disabled, carers, dla, incapacity, disabilities, jobcentre, esa
##   Lift: all-work, carersequal, ciara, dominoes, easy-read, first-aider, pre-apprenticeship
##   Score: carers, young, disabled, people, disability, allowance, youth
## Topic 33 Top Words:
##   Highest Prob: question, order, asked, mr, answer, questions, speaker
##   FREX: answer, question, questions, speaker, mr, order, deputy
##   Lift: 1080, 11.00, 11.57, 1105, 1186, 12.26, 1212
##   Score: mr, speaker, question, deputy, answer, order, questions
## Topic 34 Top Words:
##   Highest Prob: drugs, drug, road, charities, people, car, vehicles
##   FREX: crb, cannabis, bikes, barring, motor, taxi, drivers
##   Lift: 199,000, aid-style, amphetamine, angelus, barbering, barchetti, blagdon
##   Score: drug, drugs, cannabis, vehicles, charities, parking, drivers
## Topic 35 Top Words:
##   Highest Prob: international, defence, forces, world, armed, countries, foreign
##   FREX: iraq, syria, troops, nato, sierra, zimbabwe, syrian
##   Lift: 2249, 45s, afghans, alabed, aleppo, asia-pacific, ba'athist
##   Score: armed, un, military, afghanistan, syria, forces, iraq
## Topic 36 Top Words:
##   Highest Prob: home, office, immigration, uk, security, country, system
##   FREX: immigration, asylum, passport, passports, seekers, migration, nationals
##   Lift: arcs, cardholders, clandestinely, europol's, fiancées, fingerprinted, immigration
##   Score: immigration, asylum, home, passport, migration, fraud, nationals
## Topic 37 Top Words:
##   Highest Prob: house, members, debate, time, today, parliament, leader
##   FREX: house, debates, leader, debate, backbench, chamber, sides
##   Lift: vashem, yad, @donna_smiley, @jimspin, @richswitch, @timregency, @trojanfan1969
##   Score: house, debate, members, leader, parliament, motion, chamber
## Topic 38 Top Words:
##   Highest Prob: committee, report, public, review, independent, commission, select
##   FREX: select, recommendations, committees, audit, scrutiny, committee's, independent
##   Lift: 1003, 15-however, 15-which, 1905, 1992-specifies, 1993-04, 2000-which

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Score: committee, report, select, scrutiny, review, recommendations, committees

Topic 39 Top Words:

Highest Prob: wales, prison, welsh, assembly, england, prisoners, cardiff

FREX: wales, welsh, prisons, cymru, assembly, prison, prisoners

Lift: 0.48, 1,000-such, 1,009, 1,099, 1,145, 1,296, 1,500-place

Score: wales, prison, welsh, assembly, prisoners, prisons, probation

Topic 40 Top Words:

Highest Prob: european, eu, scotland, scottish, uk, union, europe

FREX: scottish, lisbon, scotland, eu, european, brexit, treaty

Lift: 07, 1-46, 1,166, 1,294, 10,182, 10.91, 10249

Score: eu, european, scottish, scotland, treaty, union, europe

Topic 41 Top Words:

Highest Prob: government, labour, conservative, government's, policy, opposition, party

FREX: conservative, conservatives, opposition, labour, government, benches, failed

Lift: cokey, draghi, moira's, 1-of, 1,057, 1.14, 1228

Score: government, conservative, labour, party, opposition, conservatives, policy

Topic 42 Top Words:

Highest Prob: staff, workers, work, training, employers, pay, working

FREX: dentists, dental, dentistry, employers, contract, contracts, workers

Lift: concentrix, dentistry, dentists, lldc, #i'm, 1-who, 1.03

Score: employers, dentists, staff, workers, dental, contract, contracts

Topic 43 Top Words:

Highest Prob: constituency, council, area, centre, residents, west, north

FREX: petitioners, declares, petition, immingham, swindon, county, lincolnshire

Lift: 1950son, a49, annesley, binnie, brancepeth, picturehouse, thelwall

Score: petitioners, petition, residents, constituency, county, yorkshire, council

Topic 44 Top Words:

Highest Prob: making, access, decision, decisions, make, made, interests

FREX: broadband, decisions, decision, making, access, criteria, powerful

Lift: 0844, 1-will, 1,000-by, 1059, 12-are, 123991, 126382

Score: decision, decisions, access, making, broadband, digital, crawley

Topic 45 Top Words:

Highest Prob: bill, clause, amendment, new, amendments, legislation, act

FREX: clause, amendment, amendments, nos, insert, clauses, provisions

Lift: #185, #85, 1-competences, 1-impact, 1-sale, 10-application, 10-changes

Score: clause, amendment, amendments, bill, lords, provisions, nos

Topic 46 Top Words:

Highest Prob: private, sector, public, tenants, landlords, property, rent

FREX: private, hmos, landlords, bedroom, tenants, letting, privately

Lift: 88.85, accommodation-and, afon, bron, condensation, hoogstraten, landlords-there

Score: private, sector, landlords, tenants, rented, rent, bedroom

Topic 47 Top Words:

Highest Prob: cases, court, legal, justice, case, criminal, law

FREX: cps, defendants, defendant, tpims, courts, court, attorney-general

Lift: intercept, 1,046, 1,237, 1,368, 1,878, 104961, 109648

Score: court, offence, courts, criminal, offences, prosecution, rape

Topic 48 Top Words:

Highest Prob: research, science, trafficking, human, engineering, technology, stem

FREX: stem, embryonic, slavery, embryos, fss, science, census

Lift: 2,744, 45-day, benin, biomedicine, biopharmaceutical, bioscience, brothel-keeping

Score: research, science, trafficking, embryos, slavery, trafficked, slough

Topic 49 Top Words:

Highest Prob: people, want, get, one, say, think, know

FREX: think, things, say, something, going, get, want

Lift: about-one, achieved-but, again-let, amendments.hon, beginning-with, braintreejames, buck
 ## Score: people, get, think, want, things, going, say
 ## Topic 50 Top Words:
 ## Highest Prob: important, issue, point, take, need, issues, however
 ## FREX: important, issues, consider, point, issue, possible, understand
 ## Lift: academy-albeit, advocate-general-i, advocate-interruption, billion-interruption, can-enal
 ## Score: important, point, issues, issue, matter, points, lady
 ## Topic 51 Top Words:
 ## Highest Prob: constituency, people, proud, many, labour, great, speech
 ## FREX: maiden, famous, queen, pride, miners, proud, memorial
 ## Lift: 22s, aaful, aching, adventurers, allaun, austin's, baked-bean
 ## Score: maiden, constituency, labour, speaker, proud, memorial, queen
 ## Topic 52 Top Words:
 ## Highest Prob: energy, fuel, climate, change, prices, green, gas
 ## FREX: electricity, renewables, solar, ofgem, feed-in, energy, tariffs
 ## Lift: 1,105, 1,345, 106.89, 2008-12, 21p, 6,196, 807
 ## Score: energy, fuel, carbon, emissions, gas, climate, prices
 ## Topic 53 Top Words:
 ## Highest Prob: bank, debt, financial, banks, credit, advice, fees
 ## FREX: loan, lending, payday, bureaux, loans, farepak, debt
 ## Lift: 0.21, 0.33, 0.76, 0.84, 1,021, 1,025, 1,189
 ## Score: debt, banks, bank, payday, loan, loans, lending
 ## Topic 54 Top Words:
 ## Highest Prob: can, welcome, sure, aware, may, many, work
 ## FREX: welcome, aware, sure, thank, friend's, discuss, pleased
 ## Lift: 1565, 18-the, 6,563, 65s, 75-year-olds, already-the, ask-in
 ## Score: thank, aware, welcome, constituents, friend's, constituency, sure
 ## Topic 55 Top Words:
 ## Highest Prob: children, child, care, parents, families, family, children's
 ## FREX: child, adopters, children's, children, parent, adoption, child's
 ## Lift: litem, nyas, pelka, dubs, @mandatenow, #900,000, 1-regardless
 ## Score: children, child, parents, care, children's, families, adoption
 ## Topic 56 Top Words:
 ## Highest Prob: secretary, state, ministers, tell, whether, said, statement
 ## FREX: secretary, state, confirm, state's, tell, minister's, ministers
 ## Lift: secretary, 1-yes, 1,631, 1135, 17,850, 2.5bn, 2013-a
 ## Score: secretary, state, statement, confirm, state's, ministers, tell
 ## Topic 57 Top Words:
 ## Highest Prob: london, mayor, property, estate, market, value, tickets
 ## FREX: leaseholders, leasehold, leases, touts, freehold, londoners, boroughs
 ## Lift: alg, all-staff, annington, aplenty, assignee, chrysalis, commonhold
 ## Score: london, leaseholders, tickets, mayor, leasehold, boroughs, ticket
 ## Topic 58 Top Words:
 ## Highest Prob: local, authorities, authority, areas, area, consultation, services
 ## FREX: authorities, authority, local, consultation, locally, strategic, councils
 ## Lift: appeal-a, central-local, laa, maas, place-shaping, placemaking, pps10
 ## Score: local, authorities, authority, councils, consultation, communities, areas
 ## Topic 59 Top Words:
 ## Highest Prob: small, business, businesses, office, post, offices, royal
 ## FREX: mail, offices, sub-post, post, businesses, small, medium-sized
 ## Lift: sub-post, #1.8, #10,000, #210, #450, #57, 1,352
 ## Score: businesses, business, post, small, offices, mail, postal
 ## Topic 60 Top Words:
 ## Highest Prob: agree, given, accept, absolutely, totally, unacceptable, surely

```
##      FREX: agree, given, accept, absolutely, mentions, totally, describes
##      Lift: agree, mentions, given, describes, totally, accept, describing
##      Score: agree, given, accept, absolutely, mentions, totally, unacceptable
```

4.3.3 Full topic model estimate summary - K60

```
##
## Call:
## estimateEffect(formula = 1:60 ~ short_list, stmobj = topic_model_k60,
##   metadata = lab_corpus_fem_stm$meta, uncertainty = "Global")
##
##
## Topic 1:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0130356  0.0002895   45.03 <0.0000000000000002 ***
## short_listTRUE -0.0031243  0.0003352   -9.32 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 2:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0121074  0.0003376   35.861 < 0.0000000000000002 ***
## short_listTRUE -0.0020867  0.0004262   -4.896    0.000000982 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0167089  0.0003705   45.093 < 0.0000000000000002 ***
## short_listTRUE 0.0011236  0.0004236    2.653    0.00799 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0140812  0.0004804   29.313 <0.0000000000000002 ***
## short_listTRUE 0.0002011  0.0005546    0.363    0.717
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 5:
```

```

##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0210630   0.0005018  41.977 <0.0000000000000002 ***
## short_listTRUE -0.0060002   0.0006145  -9.764 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 6:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0255919   0.0004125  62.046 < 0.0000000000000002 ***
## short_listTRUE 0.0025430   0.0005378   4.729    0.00000226 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0039756   0.0001851  21.479 < 0.0000000000000002 ***
## short_listTRUE 0.0007480   0.0002303   3.248    0.00116 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 8:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0061410   0.0003448  17.81 <0.0000000000000002 ***
## short_listTRUE 0.0065008   0.0004831  13.46 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 9:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0062970   0.0003206  19.644 < 0.0000000000000002 ***
## short_listTRUE 0.0019969   0.0003990   5.005    0.00000056 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0175424   0.0004530  38.722 < 0.0000000000000002 ***

```

```

## short_listTRUE -0.0031606  0.0005698  -5.547          0.0000000291 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0108525  0.0003348   32.41 <0.0000000000000002 ***
## short_listTRUE 0.0047576  0.0003989   11.93 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 12:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0263139  0.0006086   43.233 < 0.0000000000000002 ***
## short_listTRUE -0.0045794  0.0007098   -6.452    0.000000000111 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0053993  0.0002626   20.562 < 0.0000000000000002 ***
## short_listTRUE 0.0022089  0.0003209    6.883    0.00000000000592 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0131856  0.0003492   37.760 < 0.0000000000000002 ***
## short_listTRUE -0.0025186  0.0004211   -5.981    0.000000000223 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0227012  0.0004300   52.795 <0.0000000000000002 ***
## short_listTRUE -0.0045774  0.0004731   -9.676 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

```

```

##
## Topic 16:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0218774  0.0004836  45.235 <0.0000000000000002 ***
## short_listTRUE -0.0006740  0.0005843  -1.154      0.249
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 17:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0203210  0.0003532  57.542 < 0.0000000000000002 ***
## short_listTRUE -0.0015066  0.0004179  -3.605      0.000312 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0089772  0.0003524  25.477 <0.0000000000000002 ***
## short_listTRUE 0.0006035  0.0004127   1.462      0.144
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 19:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0190550  0.0005440  35.031 < 0.0000000000000002 ***
## short_listTRUE 0.0035247  0.0006941   5.078      0.000000382 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0136581  0.0005050  27.047 < 0.0000000000000002 ***
## short_listTRUE 0.0042600  0.0006825   6.242      0.000000000435 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:

```

```

##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0132462  0.0004071  32.537 <0.0000000000000002 ***
## short_listTRUE -0.0001299  0.0005103  -0.255          0.799
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 22:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0196843  0.0005820  33.82 <0.0000000000000002 ***
## short_listTRUE 0.0108667  0.0007211  15.07 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 23:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0092179  0.0004292  21.478 < 0.0000000000000002 ***
## short_listTRUE 0.0023051  0.0005383   4.282          0.0000185 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0075456  0.0003089  24.428 < 0.0000000000000002 ***
## short_listTRUE 0.0017516  0.0003655   4.792          0.00000165 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 25:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0131871  0.0004233  31.154 < 0.0000000000000002 ***
## short_listTRUE -0.0013547  0.0004817  -2.812          0.00492 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0103628  0.0003344  30.989 < 0.0000000000000002 ***
## short_listTRUE -0.0011200  0.0004319  -2.593          0.00951 **
## ---

```



```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0116682  0.0003874  30.119 < 0.0000000000000002 ***
## short_listTRUE 0.0034886  0.0004618   7.555  0.0000000000000425 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 28:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0109601  0.0003373  32.496 < 0.0000000000000002 ***
## short_listTRUE 0.0028728  0.0004072   7.055  0.000000000000174 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0170833  0.0004570  37.382 < 0.0000000000000002 ***
## short_listTRUE 0.0034700  0.0005895   5.886  0.000000000397 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 30:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0213864  0.0001850 115.620 <0.0000000000000002 ***
## short_listTRUE 0.0002594  0.0002432   1.066  0.286
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 31:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0208955  0.0003012  69.371 <0.0000000000000002 ***
## short_listTRUE 0.0005343  0.0003622   1.475  0.14
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 32:

```

```

##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0196035  0.0004519  43.38 <0.0000000000000002 ***
## short_listTRUE 0.0058534  0.0005173   11.31 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 33:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0154476  0.0003313  46.629 < 0.0000000000000002 ***
## short_listTRUE 0.0023215  0.0003823   6.073    0.00000000126 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 34:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0096921  0.0003712  26.109 <0.0000000000000002 ***
## short_listTRUE -0.0008222  0.0004489  -1.832    0.067 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 35:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.02396334  0.00062177  38.540 <0.0000000000000002 ***
## short_listTRUE -0.00005474  0.00079129  -0.069    0.945
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 36:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0160686  0.0004439  36.198 < 0.0000000000000002 ***
## short_listTRUE -0.0024379  0.0005424  -4.495    0.00000697 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 37:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0168682  0.0002538  66.47 <0.0000000000000002 ***

```

```

## short_listTRUE 0.0037566 0.0003285 11.43 <0.0000000000000002 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 38:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0239490  0.0003886  61.630 < 0.0000000000000002 ***
## short_listTRUE -0.0016639  0.0004810  -3.459      0.000542 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 39:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0075328  0.0003342  22.543 <0.0000000000000002 ***
## short_listTRUE 0.0035151  0.0003965   8.866 <0.0000000000000002 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 40:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0220762  0.0004789  46.095 <0.0000000000000002 ***
## short_listTRUE -0.0036925  0.0005579  -6.619      0.00000000000364 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 41:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0246530  0.0002863  86.101 <0.0000000000000002 ***
## short_listTRUE 0.0005338  0.0003648   1.463      0.143
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 42:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0176333  0.0004489  39.281 <0.0000000000000002 ***
## short_listTRUE -0.0031295  0.0005249  -5.962      0.0000000025 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

```

```

##
## Topic 43:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0117572  0.0004180  28.128 < 0.0000000000000002 ***
## short_listTRUE 0.0037997  0.0005189   7.323  0.000000000000245 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 44:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0091579  0.0001369  66.878 < 0.0000000000000002 ***
## short_listTRUE -0.0004890  0.0001665  -2.937    0.00331 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 45:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0318724  0.0006102  52.237 < 0.0000000000000002 ***
## short_listTRUE -0.0048532  0.0007390  -6.567    0.00000000000515 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 46:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0066483  0.0002652  25.071 <0.0000000000000002 ***
## short_listTRUE 0.0033293  0.0003469   9.598 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 47:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0307930  0.0005910  52.10 <0.0000000000000002 ***
## short_listTRUE -0.0133605  0.0007698  -17.36 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 48:
##
## Coefficients:

```

```

##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0086589  0.0003002   28.85 < 0.0000000000000002 ***
## short_listTRUE -0.0010061  0.0003672   -2.74      0.00614 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 49:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0438249  0.0003998  109.604 < 0.0000000000000002 ***
## short_listTRUE 0.0026586  0.0004736    5.613      0.0000000199 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 50:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0557459  0.0003515  158.61 <0.0000000000000002 ***
## short_listTRUE -0.0144767  0.0004300  -33.67 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 51:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0099013  0.0003703   26.74 < 0.0000000000000002 ***
## short_listTRUE 0.0017971  0.0004667    3.85      0.000118 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 52:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0184049  0.0005324   34.573 < 0.0000000000000002 ***
## short_listTRUE -0.0039479  0.0006943   -5.686      0.000000013 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 53:
##
## Coefficients:
##               Estimate Std. Error t value          Pr(>|t|)
## (Intercept)    0.0110253  0.0003820   28.865 < 0.0000000000000002 ***
## short_listTRUE 0.0028302  0.0004743    5.967      0.00000000243 ***
## ---

```

```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 54:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0266584  0.0002005 132.971 <0.0000000000000002 ***
## short_listTRUE 0.0001294  0.0002498   0.518      0.604
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 55:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0174581  0.0004880  35.774 <0.0000000000000002 ***
## short_listTRUE -0.0008222  0.0005870  -1.401      0.161
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 56:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0165708  0.0003141  52.75 <0.0000000000000002 ***
## short_listTRUE 0.0075543  0.0003989  18.94 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 57:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0066504  0.0002757  24.12 < 0.0000000000000002 ***
## short_listTRUE 0.0014064  0.0003349   4.20    0.0000267 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 58:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0270018  0.0003675  73.48 <0.0000000000000002 ***
## short_listTRUE -0.0097526  0.0004523 -21.56 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 59:

```

```
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0123960  0.0003468  35.740 < 0.0000000000000002 ***
## short_listTRUE -0.0027881  0.0003937  -7.081    0.000000000000144 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 60:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.00382579 0.00003760 101.76 <0.0000000000000002 ***
## short_listTRUE 0.00064400 0.00004708  13.68 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

4.4 K0

4.4.1 Shortlists vs Non-Shortlists - k0

The first implementation used an algorithm developed by Lee & Mimno (2014), implemented in the `stm` package (Roberts et al., 2018), to estimate the number of topics across all speeches made by female Labour MPs, using the “spectral” method developed by Arora et al. (2013), implemented by Roberts et al. (2018). The resulting topic model has 84 topics, across 81,607 documents and a dictionary of 115,477 words. However, the topic quality with $K = 84$ is poor, and several topics have poor semantic coherence (see 21).

There are several clusters of topics in 20. For instance, we can see the closeness of Topic 15 (unemployment) and Topic 43 (housing), as both are social issues include discussions of budgets and costs, while Topics 23 (bill amendments) and 16 (education) are very far apart.

THIS NEEDS TO BE RUN

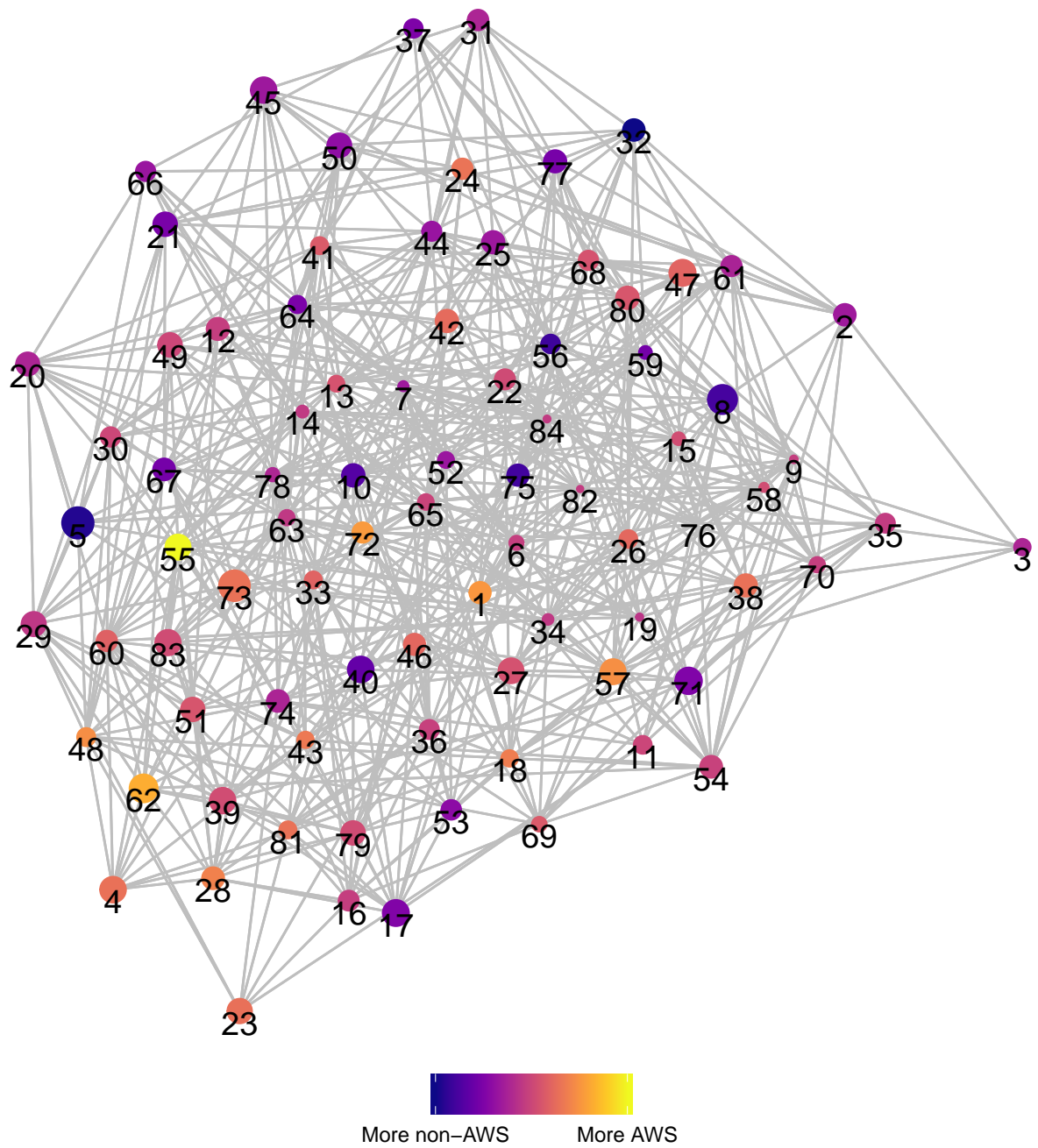


Figure 20: Fruchterman-Reingold plot of k0 Network

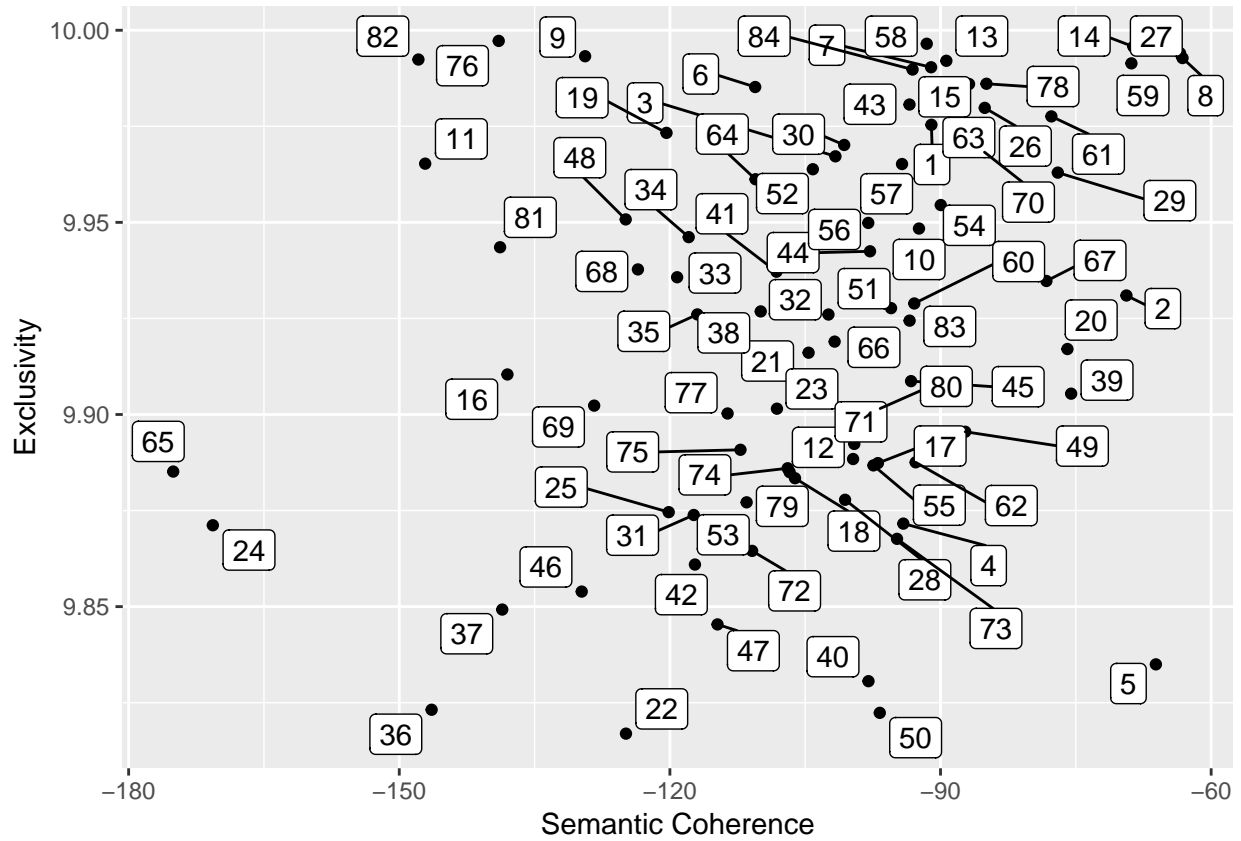


Figure 21: Coherence of k0 Topic Models

Table 19: Count and Distribution of Topics – k0

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
Topic 1	800	1.49%	249	0.89%	2,245	1.33%
Topic 2	699	1.3%	397	1.42%	3,275	1.93%
Topic 3	264	0.49%	218	0.78%	1,012	0.6%
Topic 4	1,255	2.33%	506	1.82%	1,979	1.17%
Topic 5	1,601	2.98%	1,342	4.82%	4,025	2.38%
Topic 6	218	0.41%	74	0.27%	351	0.21%
Topic 7	45	0.08%	25	0.09%	121	0.07%
Topic 8	1,287	2.39%	1,142	4.1%	7,256	4.28%
Topic 9	10	0.02%	2	0.01%	9	0.01%
Topic 10	699	1.3%	527	1.89%	2,151	1.27%
Topic 11	421	0.78%	202	0.72%	1,292	0.76%
Topic 12	744	1.38%	440	1.58%	350	0.21%
Topic 13	341	0.63%	97	0.35%	672	0.4%
Topic 14	98	0.18%	54	0.19%	536	0.32%
Topic 15	138	0.26%	57	0.2%	382	0.23%
Topic 16	538	1%	331	1.19%	1,757	1.04%
Topic 17	1,023	1.9%	801	2.87%	4,076	2.41%

Table 19: Count and Distribution of Topics – k0 (*continued*)

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
Topic 18	373	0.69%	110	0.39%	1,019	0.6%
Topic 19	5	0.01%	2	0.01%	NA	NA%
Topic 20	848	1.58%	469	1.68%	1,402	0.83%
Topic 21	832	1.55%	573	2.06%	2,731	1.61%
Topic 22	611	1.14%	283	1.02%	1,462	0.86%
Topic 23	1,125	2.09%	414	1.49%	2,779	1.64%
Topic 24	687	1.28%	236	0.85%	1,522	0.9%
Topic 25	743	1.38%	465	1.67%	1,841	1.09%
Topic 26	462	0.86%	144	0.52%	2,383	1.41%
Topic 27	1,183	2.2%	435	1.56%	5,936	3.51%
Topic 28	876	1.63%	254	0.91%	1,986	1.17%
Topic 29	1,013	1.88%	484	1.74%	3,881	2.29%
Topic 30	523	0.97%	275	0.99%	1,860	1.1%
Topic 31	582	1.08%	367	1.32%	586	0.35%
Topic 32	460	0.86%	639	2.29%	2,648	1.56%
Topic 33	417	0.78%	109	0.39%	1,330	0.79%
Topic 34	61	0.11%	31	0.11%	25	0.01%
Topic 35	506	0.94%	242	0.87%	1,661	0.98%
Topic 36	490	0.91%	272	0.98%	1,303	0.77%
Topic 37	346	0.64%	347	1.25%	757	0.45%
Topic 38	915	1.7%	279	1%	4,972	2.94%
Topic 39	1,149	2.14%	582	2.09%	4,542	2.68%
Topic 40	974	1.81%	780	2.8%	4,241	2.5%
Topic 41	434	0.81%	109	0.39%	583	0.34%
Topic 42	884	1.64%	331	1.19%	4,092	2.42%
Topic 43	363	0.67%	105	0.38%	1,011	0.6%
Topic 44	452	0.84%	316	1.13%	1,521	0.9%
Topic 45	1,103	2.05%	633	2.27%	1,659	0.98%
Topic 46	756	1.41%	285	1.02%	3,008	1.78%
Topic 47	1,291	2.4%	544	1.95%	5,110	3.02%
Topic 48	514	0.96%	129	0.46%	1,020	0.6%
Topic 49	932	1.73%	489	1.76%	1,067	0.63%
Topic 50	848	1.58%	592	2.12%	2,617	1.55%
Topic 51	953	1.77%	425	1.53%	2,233	1.32%
Topic 52	275	0.51%	161	0.58%	834	0.49%
Topic 53	474	0.88%	350	1.26%	1,408	0.83%
Topic 54	774	1.44%	363	1.3%	4,265	2.52%
Topic 55	1,429	2.66%	208	0.75%	1,604	0.95%
Topic 56	263	0.49%	438	1.57%	1,597	0.94%
Topic 57	1,314	2.44%	328	1.18%	5,316	3.14%
Topic 58	40	0.07%	NA	NA%	37	0.02%
Topic 59	113	0.21%	88	0.32%	474	0.28%
Topic 60	676	1.26%	251	0.9%	1,055	0.62%
Topic 61	555	1.03%	351	1.26%	2,610	1.54%

Table 19: Count and Distribution of Topics – k0 (*continued*)

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
Topic 62	1,633	3.04%	543	1.95%	4,237	2.5%
Topic 63	242	0.45%	144	0.52%	428	0.25%
Topic 64	308	0.57%	261	0.94%	873	0.52%
Topic 65	300	0.56%	113	0.41%	747	0.44%
Topic 66	465	0.86%	325	1.17%	682	0.4%
Topic 67	616	1.15%	509	1.83%	2,270	1.34%
Topic 68	541	1.01%	246	0.88%	1,468	0.87%
Topic 69	225	0.42%	102	0.37%	547	0.32%
Topic 70	255	0.47%	132	0.47%	1,416	0.84%
Topic 71	1,143	2.13%	779	2.8%	5,695	3.36%
Topic 72	726	1.35%	200	0.72%	1,060	0.63%
Topic 73	1,974	3.67%	827	2.97%	6,342	3.75%
Topic 74	704	1.31%	425	1.53%	2,272	1.34%
Topic 75	523	0.97%	540	1.94%	2,441	1.44%
Topic 77	675	1.25%	517	1.86%	2,741	1.62%
Topic 78	160	0.3%	75	0.27%	236	0.14%
Topic 79	982	1.83%	415	1.49%	3,243	1.92%
Topic 80	903	1.68%	328	1.18%	3,132	1.85%
Topic 81	434	0.81%	99	0.36%	1,199	0.71%
Topic 82	2	0%	1	0%	NA	NA%
Topic 83	1,172	2.18%	525	1.88%	2,834	1.67%
Topic 84	NA	NA%	5	0.02%	1	0%

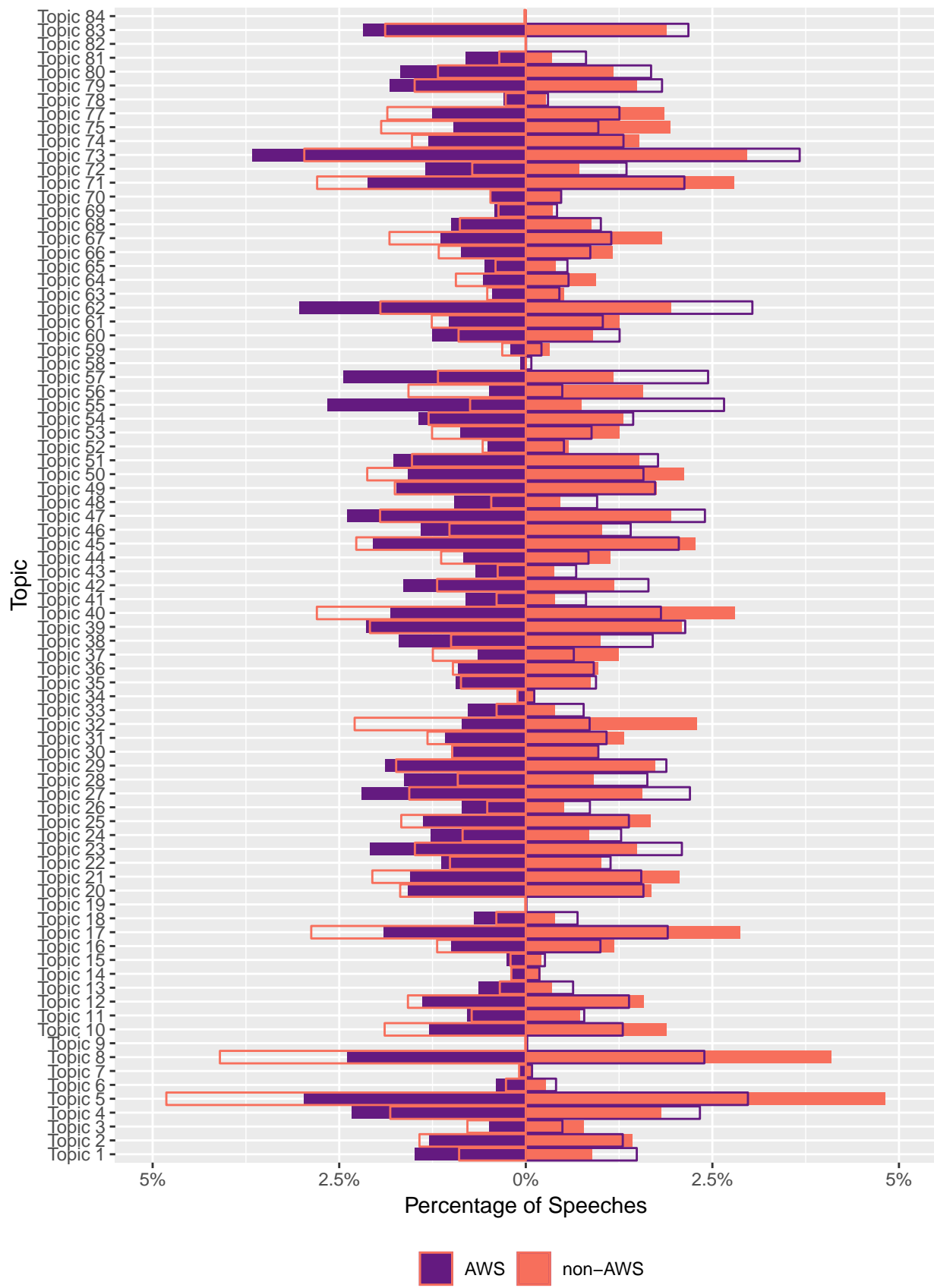


Figure 22: k0 Pyramid Chart

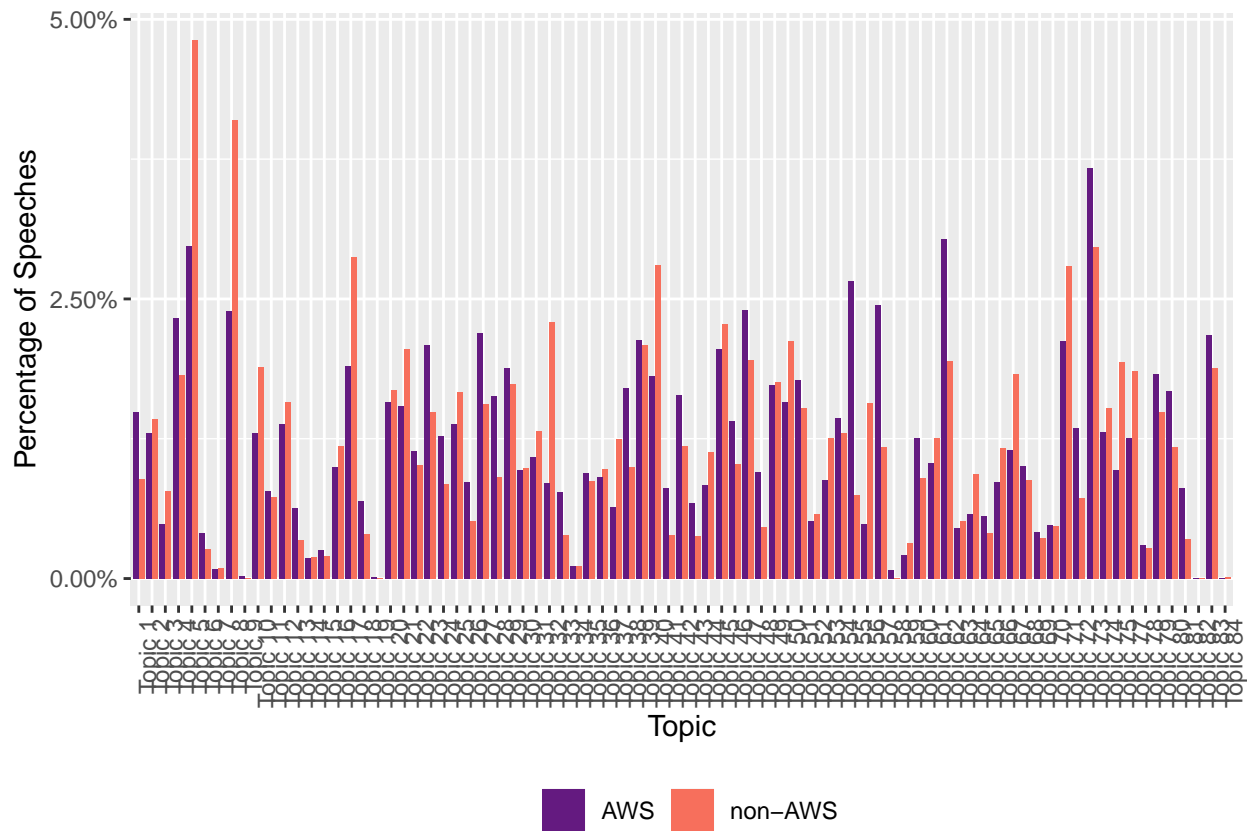


Figure 23: k0 Bar Chart

4.4.1.1 Word Occurences

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

Table 20: Words in topic - k0

Topic Number	Top Ten Words	Top Ten FREX
Topic 1	secretary, state, ministers, tell, home, department, confirm, explain, said, today, now, us, office, chief, state's, announcement, yet, says, given, told	secretary, state, confirm, ministers, state's, tell, explain, clarify, assurances, announcement, update, talks, cabinet, chaos, conversations, expects, commit, please, u-turn, under-secretary
Topic 2	clause, amendment, amendments, new, clauses, tabled, committee, government, 1, provisions, 2, lords, provision, part, regulations, power, schedule, 3, 5, ensure	nos, amendments, clause, clauses, schedule, tabled, amendment, commencement, drafting, consequential, affirmative, proceedings, wording, provisions, exemption, tabling, drafted, technical, 5, paragraph

Table 20: Words in topic - k0 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 3	move, second, read, leave, line, agreed, reading, lords, beg, end, page, notes, agrees, b, time, amendment, shall, 1, 2, insert	page, beg, read, insert, reading, agrees, move, b, welcomes, notes, second, agreed, leave, disagrees, withdraw, lords, ordered, line, thereof, closurestanding
Topic 4	housing, homes, private, social, affordable, accommodation, home, rent, sector, tenants, properties, need, landlords, rented, property, homelessness, buy, families, homeless, council	tenants, landlords, rented, homelessness, homeless, rents, tenancies, tenancy, rent, housing, hmos, one-bedroom, affordable, accommodation, properties, associations, landlord, homes, tenant, rough
Topic 5	nhs, hospital, patients, staff, trust, hospitals, health, service, services, doctors, trusts, patient, nurses, new, care, emergency, medical, e, waiting, gp	dentists, dental, dentistry, hospitals, hospital, nurses, pct, nhs, e, trusts, doctors, junior, ambulance, reconfiguration, dentist, reorganisation, pcts, midwives, acute, gp
Topic 6	make, sure, policy, statement, progress, plans, difference, future, towards, responsibilities, government's, easier, statements, commitments, milton, keynes, departmental, reference, clear, announcements	make, statement, sure, progress, policy, difference, plans, departmental, milton, easier, responsibilities, keynes, commitments, towards, statements, announcements, future, autumn, reference, clearer
Topic 7	can, ensure, welcome, work, aware, continue, done, ensuring, commitment, especially, assure, friend's, share, colleagues, recently, offer, closely, working, throughout, particularly	ensure, aware, welcome, can, friend's, assure, ensuring, continue, closely, especially, commitment, reassure, done, share, welcomed, assurance, colleagues, confident, offer, continuing
Topic 8	issues, hope, however, must, consider, understand, matter, deal, take, possible, concerns, forward, may, place, shall, concern, raised, look, able, certainly	issues, consider, understand, matter, concerns, possible, certainly, hope, concern, forward, raised, considering, carefully, matters, deal, proper, shall, properly, concerned, expressed
Topic 9	agree, making, absolutely, rather, completely, entirely, argument, whatever, step, message, precisely, fact, powerful, totally, send, direction, lead, suggests, unacceptable, crucial	agree, absolutely, making, completely, entirely, precisely, argument, whatever, totally, message, powerful, send, rather, direction, mentions, danger, describes, step, suggests, unfortunate
Topic 10	community, communities, organisations, work, role, sector, voluntary, together, partnership, groups, play, new, social, working, society, involved, develop, project, opportunities, areas	voluntary, community, partnership, organisations, play, communities, co-operative, role, partnerships, together, innovative, involvement, groups, develop, volunteers, sector, project, volunteering, projects, facilities
Topic 11	air, airport, indicated, airports, heathrow, aviation, noise, reconsider, environmental, pollution, security, flights, passengers, expansion, safety, capacity, assent, aircraft, gatwick, uk	aviation, flights, gatwick, dissent, airlines, runway, caa, apd, airports, airport, heathrow, indicated, air, noise, nats, pollution, reconsider, assent, prestwick, baa

Table 20: Words in topic - k0 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 12	women, men, women's, pay, woman, gender, equal, equality, girls, female, gap, many, age, male, still, discrimination, work, labour, day, society	women, shortlists, gender, women's, all-women, men, female, male, bishops, men's, waspi, girls, equal, sanitary, woman, fawcett, pregnant, equalities, feminist, woman's
Topic 13	made, number, clear, impact, changes, recent, assessment, review, effect, level, discussions, change, proposed, likely, potential, representations, effects, implications, levels, estimate	made, recent, assessment, changes, impact, representations, discussions, clear, effect, number, estimate, implications, level, regarding, effects, review, proposed, department's, potential, likely
Topic 14	years, now, two, three, past, months, 10, ago, next, just, five, four, times, weeks, six, days, half, almost, 20, 30	years, three, past, ago, months, two, four, five, 10, weeks, now, six, next, half, days, times, seven, eight, 30, almost
Topic 15	whether, question, given, thank, ask, asked, put, answer, questions, response, grateful, earlier, giving, learned, knows, minister's, written, press, asking, received	answer, question, ask, questions, thank, asked, grateful, whether, answers, written, response, knows, asking, minister's, answered, learned, write, answering, giving, earlier
Topic 16	post, office, petition, offices, closure, rural, royal, mail, petitioners, residents, service, services, network, closures, house, request, dog, therefore, commons, dogs	petition, petitioners, sub-post, sub-postmasters, offices, mail, declares, post, consignia, postcomm, closures, closure, urges, etc, signatures, postwatch, basildon, dog, branches, branch
Topic 17	energy, climate, water, change, fuel, companies, bills, prices, green, carbon, market, power, gas, electricity, price, efficiency, emissions, wind, new, winter	energy, renewables, solar, ofgem, feed-in, electricity, carbon, generators, renewable, wind, shale, climate, tariff, ofwat, energy-efficient, decarbonisation, fuel, water, meters, tariffs
Topic 18	constituency, constituents, many, great, proud, speech, represent, mine, new, constituencies, town, campaign, labour, also, mp, like, hackney, hope, south, maiden	maiden, constituency, hackney, mine, constituents, mp, swindon, halifax, constituencies, cleethorpes, represent, predecessor, gracious, burnley, grimsby, shoreditch, proud, predecessors, pride, famous
Topic 19	want, go, really, wants, putting, ahead, prepared, urge, end, beyond, put, allowed, solution, hold, push, easily, outside, real, walk, oh	really, go, want, wants, prepared, ahead, putting, oh, bits, push, conversation, easily, beyond, walk, solution, dear, wanting, urge, sounds, likes
Topic 20	health, care, services, social, mental, service, need, problems, needs, older, national, home, provide, provision, quality, primary, commissioning, professionals, elderly, adult	mental, health, care, suicide, commissioning, services, discharge, discharges, intermediate, psychiatric, social, professionals, healthwatch, wellbeing, adolescent, older, packages, illness, residential, camhs

Table 20: Words in topic - k0 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 21	police, officers, crime, policing, home, force, fire, forces, officer, chief, service, neighbourhood, community, cuts, serious, public, numbers, resources, work, constable	constables, officers, policing, constable, police, soca, fire, firefighters, pcsos, neighbourhood, constabulary, officer, hmic, metropolitan, front-line, crime, beat, incidents, pc, teams
Topic 22	marriage, church, ethnic, black, minority, faith, religious, community, many, law, society, communities, country, gay, couples, religion, freedom, forced, civil, muslim	gay, same-sex, humanist, marriage, holocaust, church, religious, ethnic, marriages, bisexual, transgender, asian, hatred, religion, faiths, lesbian, faith, racism, marry, sexuality
Topic 23	transport, bus, rail, services, travel, train, line, service, fares, network, passengers, trains, public, buses, main, operators, coast, railway, use, station	bus, fares, buses, concessionary, franchising, railtrack, fare, trains, railways, rail, electrification, train, commuters, journeys, railway, transport, franchise, tolls, coast, travel
Topic 24	smoking, ban, charities, animals, food, charity, health, tobacco, advertising, animal, products, public, welfare, smoke, use, fireworks, evidence, dogs, gift, industry	tobacco, fur, mink, circuses, sunbeds, sunbed, snares, smoking, animals, smoke, obesity, fireworks, hunting, smokers, ban, animal, smoke-free, puppies, gift, labelling
Topic 25	home, immigration, uk, country, asylum, office, system, british, refugees, identity, border, migration, passport, britain, rules, foreign, illegal, cards, seekers, citizens	immigration, asylum, seekers, passports, nationality, migration, passport, migrants, refugees, id, biometric, identity, deported, visa, nationals, deportation, refugee, visas, border, cards
Topic 26	said, us, even, let, enough, wrong, simply, saying, never, told, fact, thought, nothing, seems, say, believe, says, still, anything, happened	wrong, let, thought, saying, anything, seems, though, got, nothing, never, enough, surely, happened, even, anyone, went, nobody, word, changed, simply
Topic 27	get, know, think, say, much, see, going, just, like, things, come, back, problem, find, might, something, look, us, better, can	get, going, things, think, something, lot, talking, say, trying, see, know, talk, thing, find, getting, quite, come, happening, much, sort
Topic 28	debt, banks, bank, credit, financial, fees, pay, advice, money, loan, loans, interest, banking, companies, lending, cost, consumer, charges, mortgage, many	payday, lending, loans, farepak, loan, banks, lenders, fees, debt, debts, rbs, banking, mortgage, bank, mortgages, fca, borrowers, timeshare, bankers, high-cost
Topic 29	million, funding, money, cuts, increase, extra, year, spending, billion, cut, additional, fund, cost, budget, costs, spent, investment, grant, resources, already	funding, million, grant, formula, spending, extra, expenditure, money, allocated, budgets, billion, fund, spent, cuts, additional, grants, spend, real-terms, funds, 2007-08
Topic 30	year, since, last, report, figures, number, said, official, april, march, show, 2010, published, end, figure, month, january, october, 25, june	march, january, october, official, 2011, figures, november, december, vol, since, april, june, year, july, february, september, figure, 2008, month, latest

Table 20: Words in topic - k0 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 31	abuse, children, protection, child, sexual, vulnerable, trafficking, sex, home, online, exploitation, victims, protect, need, risk, safe, cases, also, internet, missing	pornography, barring, crb, trafficked, abuse, grooming, trafficking, exploitation, stalking, barred, abused, safeguarding, sex, prostitution, bullying, fgm, abusers, survivors, slavery, images
Topic 32	act, person, offence, order, law, orders, powers, reasonable, circumstances, section, control, can, power, whether, criminal, used, use, test, may, might	orders, offence, reasonable, person, tpims, proportionate, surveillance, safeguards, liberty, lawful, definition, intercept, reviewer, reasonably, beaconsfieldmr, suspects, unlawful, penalties, premises, jurisdiction
Topic 33	sport, football, club, clubs, sports, games, event, tickets, olympics, events, market, swimming, olympic, music, media, ticket, culture, league, fans, team	touts, games, olympic, football, copyright, olympics, sport, sports, club, swimming, lap-dancing, sporting, rugby, basketball, clubs, cup, fans, tickets, stadium, prs
Topic 34	good, best, bad, called, practice, tories, examples, old, must, challenge, century, news, modern, ideas, luton, deal, change, example, better, 21st	good, bad, tories, luton, ideas, examples, 21st, luck, century, grasp, called, hat, old, dynamic, sound, modern, constant, practice, best, spread
Topic 35	parliament, scotland, scottish, united, kingdom, devolution, uk, devolved, england, glasgow, english, executive, snp, powers, aberdeen, edinburgh, administrations, rest, government, ayrshire	scotland, scottish, snp, scotland's, holyrood, calman, vellum, administrations, scots, ayrshire, devolved, glasgow, perthshirepete, devolution, parliament, stirling, wishart, perth, dundee, barnett
Topic 36	bristol, arts, national, great, heritage, many, area, tourism, museum, engineering, cultural, visit, creative, countryside, forest, culture, centre, visitors, also, british	museum, arts, gospels, morecambe, bristol, heritage, museums, seaside, tourism, lincoln, tourist, sssis, resorts, dance, bay, restoration, cockle, peat, beach, dean
Topic 37	research, medical, science, use, stem, human, health, blood, cell, consent, scientific, cells, many, tissue, used, also, pregnancy, embryos, disease, may	embryos, abortion, hepatitis, cloning, organs, abortions, embryonic, piercing, co-proxamol, anaemia, embryology, hfea, primodos, transplantation, tissue, b12, sickle, embryo, cell, stem
Topic 38	vote, political, election, parties, elected, parliament, democracy, elections, electoral, voting, politics, system, register, general, democratic, referendum, party, commission, chamber, registration	electoral, vote, voting, elections, voters, votes, democracy, political, politics, polling, electorate, candidates, elected, election, democratic, ballot, turnout, hereditary, politicians, voter
Topic 39	economy, economic, jobs, growth, investment, chancellor, budget, sector, public, unemployment, long-term, future, billion, deficit, recession, plan, need, cuts, private, spending	recession, economy, growth, productivity, deficit, obr, gdp, forecast, forecasts, unemployment, borrowing, chancellor, austerity, economic, boost, chancellor's, fiscal, stimulus, double-dip, recovery

Table 20: Words in topic - k0 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 40	international, countries, world, development, aid, developing, uk, country, trade, global, nations, africa, united, un, commonwealth, government, foreign, political, overseas, british	zimbabwe, burma, dfid, congo, burmese, sri, cancan, sierra, lanka, leone, sub-saharan, africa, mugabe, lankan, china, g8, burundi, commonwealth, international, doha
Topic 41	group, needs, special, learning, training, disabled, all-party, disability, disabilities, provision, autism, educational, also, support, services, hearing, sen, language, access, awareness	autism, sen, deaf, autistic, dyslexia, disabilities, special, all-party, learning, spectrum, mainstream, advocacy, educational, group, hearing, disability, transition, taskforce, asperger's, language
Topic 42	defence, forces, armed, service, personnel, military, army, royal, afghanistan, veterans, ministry, families, base, war, nuclear, british, equipment, mod, future, covenant	veterans, mod, naval, hms, reservists, submarines, regiment, battalion, dockyard, culls, armed, marines, covenant, ta, navy, personnel, cull, fusiliers, tb, regiments
Topic 43	government, government's, labour, country, previous, policies, yet, record, failed, real, crisis, seen, failure, now, despite, rise, coalition, thousands, instead, across	government, government's, previous, failed, coalition, promise, labour's, labour, reality, policies, promised, failure, promises, rising, queen's, facing, risen, failing, millions, tory
Topic 44	information, available, guidance, data, advice, details, arrangements, national, required, provide, agency, provided, officials, issued, informed, department, office, used, detailed, systems	information, data, details, guidance, accurate, issued, officials, records, requests, census, informed, reviews, detailed, check, publish, monitoring, monitor, sharing, advice, arrangements
Topic 45	violence, domestic, victims, justice, prison, rape, criminal, cases, offenders, crime, prisons, prisoners, sexual, crimes, system, prosecution, sentence, victim, probation, service	prison, probation, reoffending, prisons, rape, sentences, prisoners, violence, sentence, sentencing, offenders, cps, offender, domestic, solicitor-general, prisoner, fss, custody, conviction, victim
Topic 46	food, farmers, industry, environment, rural, oil, waste, environmental, sea, marine, fishing, uk, fish, fisheries, gas, farming, meat, agricultural, north, sustainable	fisheries, fishermen, cod, visteon, mmo, farmers, fishing, fish, oil, cfp, biofuels, marine, recycling, lpg, beef, meat, stocks, agriculture, sea, crops
Topic 47	security, peace, foreign, war, conflict, threat, syria, international, iraq, terrorism, israel, us, un, united, military, attacks, humanitarian, civilians, must, terrorist	israel, palestinian, israeli, gaza, yemen, daesh, palestinians, hamas, palestine, israelis, assad, aleppo, saddam, isil, proscription, isis, israel's, airstrikes, two-state, syria
Topic 48	london, city, north, north-east, hull, liverpool, country, areas, manchester, yorkshire, cities, west, across, east, mayor, region, greater, newcastle, south, sheffield	hull, city, north-east, mayor, london, newcastle, liverpool, yorkshire, humber, cities, tyneside, lincolnshire, powerhouse, durham, london's, manchester, tyne, boroughs, sheffield, londoners

Table 20: Words in topic - k0 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 49	children, child, parents, families, care, children's, family, start, parent, many, adoption, early, lone, centres, provision, working, child's, places, work, mothers	csa, child's, adopters, lone, parents, parent, children's, childcare, child, four-year-olds, adoption, children, looked-after, nursery, parental, mothers, adoptive, fathers, foster, placement
Topic 50	behaviour, crime, antisocial, alcohol, drugs, drug, problem, use, problems, tackle, licensing, powers, driving, street, also, drinking, misuse, used, police, disorder	alcohol, antisocial, asbos, alcohol-related, drinking, binge, misuse, cannabis, graffiti, behaviour, knife, anti-social, gang, knives, nuisance, substances, psychoactive, theft, licensing, bikes
Topic 51	scheme, pension, pensions, pensioners, schemes, insurance, savings, income, age, retirement, saving, contributions, fund, save, basic, money, credit, receive, national, system	pension, pensioners, retirement, pensions, scheme, pensioner, annuity, saving, savings, take-up, schemes, occupational, insurance, annuities, auto-enrolment, retire, isas, isa, cpi, means-testing
Topic 52	public, proposals, consultation, new, service, access, paper, white, use, proposal, civil, document, reform, set, technology, options, consult, open, internet, consulted	proposals, consultation, paper, white, document, broadband, electronic, consult, responses, consulted, consulting, public, servants, options, communications, proposal, consultations, access, internet, proposes
Topic 53	planning, land, development, new, building, site, sites, homes, built, buildings, estate, green, build, residents, use, plan, areas, housing, developments, houses	brownfield, planning, leaseholders, eco-towns, land, developers, leasehold, builders, lease, leases, site, buildings, belt, sites, estate, spaces, nppf, freehold, garden, registry
Topic 54	members, opposition, conservative, party, said, heard, hear, liberal, today, labour, conservatives, many, front, position, perhaps, listen, benches, say, back, democrats	conservative, liberal, democrats, opposition, conservatives, benches, democrat, party, bench, remind, surprised, manifesto, interruption, benchers, party's, opposed, front-bench, sorry, lib, listening
Topic 55	benefit, work, people, benefits, disabled, allowance, system, welfare, credit, universal, payments, disability, support, payment, claimants, reform, claim, assessment, pensions, employment	esa, dla, atos, claimants, incapacity, dwp, allowance, jsa, jobseeker's, disabled, universal, pip, uc, benefit, sanctioned, welfare, benefits, jobcentre, claiming, sanctions
Topic 56	case, decision, process, decisions, cases, evidence, taken, review, lord, appeal, basis, decide, individual, circumstances, application, system, whether, considered, judgment, accept	appeal, decision, judgment, decisions, case, judicial, decide, lord, appeals, application, process, proceed, criteria, judgments, delay, merits, deciding, applicant, decides, basis
Topic 57	house, debate, may, order, mr, speaker, deputy, leader, today, motion, day, business, opportunity, meeting, chamber, debates, join, yesterday, us, morning	leader, speaker, deputy, house, apologise, madam, motion, mr, backbench, tomorrow, monday, debate, order, debates, recess, tuesday, thursday, back-bench, sitting, morning

Table 20: Words in topic - k0 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 58	one, time, last, long, week, speak, later, little, another, call, every, short, come, chance, met, running, minutes, return, limit, interventions	one, time, long, call, week, short, later, last, speak, running, interventions, minutes, little, chance, missed, minute, limit, another, intervene, finished
Topic 59	important, need, point, issue, also, different, part, well, makes, particular, points, extremely, particularly, recognise, needs, approach, address, whole, gentleman's, across	important, point, different, issue, makes, extremely, points, need, recognise, particular, gentleman's, raises, approach, considerable, address, relation, part, addressed, well, wider
Topic 60	poverty, poor, social, low, living, average, poorest, areas, tackle, high, levels, target, income, food, rates, country, gap, highest, families, tackling	poverty, deprivation, poorest, poor, poorer, inequality, inequalities, low, lowest, low-income, mobility, highest, average, target, rich, affluent, relative, incomes, joseph, expectancy
Topic 61	bill, legislation, act, law, provisions, powers, introduced, place, measure, introduce, measures, regulations, private, protection, already, believe, members, allow, bill's, draft	bill, legislation, bill's, passage, provisions, legislative, draft, measure, introduce, member's, statute, introducing, legislate, regulations, introduced, seeks, stages, passed, contains, safeguards
Topic 62	tax, rate, families, pay, income, credits, chancellor, cut, budget, vat, increase, year, benefit, credit, working, paying, cost, hit, revenue, changes	tax, 50p, vat, credits, taxes, avoidance, taxation, millionaires, hmrc, exchequer, gaar, corporation, revenue, rate, allowances, earning, gains, evasion, relief, hit
Topic 63	people, young, many, lives, people's, life, age, youth, live, person, feel, need, 16, experience, must, often, future, older, 18, become	young, people, people's, youth, lives, 16, age, younger, feel, older, live, stay, 18, life, connexions, person, ordinary, 17-year-olds, many, ages
Topic 64	programme, strategy, department, national, plan, safety, key, management, programmes, priority, effective, working, work, performance, improving, improvements, including, set, risk, standards	programme, strategy, pilot, flu, performance, priority, programmes, adjourned, pilots, improvements, improving, evaluation, implementing, implementation, management, delivery, improvement, plan, vaccine, safety
Topic 65	heart, trade, unions, union, stroke, disease, slough, industrial, strike, life, today, death, members, mouth, rochdale, conditions, history, movement, many, cardiac	mesothelioma, cpr, heart, stroke, asbestos, cardiomyopathy, slough, unions, rochdale, cardiac, mouth, jo, defibrillators, slave, gmb, strokes, forestry, romford, ash, sudden
Topic 66	treatment, cancer, patients, screening, clinical, condition, disease, patient, nhs, diagnosis, drugs, pain, breast, medical, national, available, treatments, drug, gps, specialist	prostate, cervical, endometriosis, breast, screening, cancer, treatment, palliative, fibrosis, radiotherapy, cancers, diagnosis, symptoms, treatments, hospice, diagnosed, pain, hospices, nice, ectopic

Table 20: Words in topic - k0 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 67	local, authorities, council, authority, councils, area, areas, government, communities, services, county, provision, needs, power, councillors, level, central, locally, powers, duty	local, authorities, councils, authority, councillors, council, county, unitary, locally, localism, council's, lancashire, authority's, parish, councillor, district, exeter, area, norwich, boards
Topic 68	rights, wales, human, northern, ireland, commission, welsh, assembly, convention, act, equality, discrimination, commissioner, government, england, cardiff, duty, law, uk, respect	ireland, welsh, rights, assembly, wales, convention, human, northern, commissioner, cymru, discrimination, ehrc, commissions, echr, equality, assembly's, cardiff, strands, commission, belfast
Topic 69	east, st, south, friends, heard, west, birmingham, leicester, north, eastmr, smith, sunderland, helier, brent, ealing, croydon, under-secretary, speeches, jones, called	helier, cooper, bromley, stuart, croydon, ealing, castlefordyvette, ewellchris, holborn, normanton, coventry, dobson, eastmr, hayes, brent, epsom, helens, mitcham, bury, stoke-on-trent
Topic 70	member, members, debate, speech, also, spoke, mentioned, made, congratulate, talked, comments, north, remarks, raised, pointed, referred, said, follow, pleasure, excellent	member, spoke, remarks, talked, thoughtful, eloquently, pleasure, pointed, cambridgeshiremr, bermondsey, reminded, clarke, powerfully, norfolkmr, southwark, comments, passion, eloquent, congratulate, passionately
Topic 71	european, eu, union, uk, europe, states, british, countries, negotiations, treaty, us, trade, agreement, united, britain, foreign, council, single, country, national	treaty, lisbon, european, eu, accession, brexit, euro, negotiations, enlargement, europe, gibraltar, negotiating, brussels, eurozone, sovereignty, directive, currency, treaties, meps, esm
Topic 72	carers, family, constituent, told, families, life, home, caring, day, mother, many, man, lives, mrs, person, case, died, hours, week, can	carers, constituent, dementia, caring, mrs, husband, son, carer, daughter, mum, mother, wife, contacted, loved, father, respite, died, dad, sister, stories
Topic 73	schools, education, school, teachers, students, university, children, pupils, skills, college, primary, teaching, higher, standards, system, universities, learning, colleges, training, free	schools, teachers, academies, grammar, fe, gcse, pupils, school, post-16, students, teaching, pupil, education, leas, academy, colleges, academisation, teacher, curriculum, gcse
Topic 74	regional, development, road, investment, transport, new, economic, infrastructure, regeneration, project, regions, region, roads, major, projects, north-west, speed, traffic, link, area	hs2, regional, rdas, high-speed, rda, crossrail, regeneration, roads, cycling, north-west, regions, cornwall, connectivity, road, freight, motorway, speed, essex, highways, inward
Topic 75	company, companies, financial, regulation, standards, competition, regulatory, market, regime, services, code, business, system, consumers, fsa, rules, sector, also, assets, set	policyholders, fsa, regulatory, corporate, ombudsman, regulators, liabilities, equitable, competition, shares, rock, penrose, code, regulation, shareholders, auditors, liability, assets, directors, regulator

Table 20: Words in topic - k0 (*continued*)

Topic Number	Top Ten Words	Top Ten FREX
Topic 76	course, indeed, lady, meet, happy, note, glad, understanding, intend, correct, round, shortly, brief, briefly, intention, generous, lady's, asks, stress, finds	lady, course, indeed, happy, note, glad, lady's, brief, correct, intend, meet, shortly, round, understanding, tibshelf, asks, briefly, generous, betws, deincourt
Topic 77	legal, court, justice, courts, inquiry, investigation, cases, law, aid, complaints, mr, system, advice, case, families, trial, family, evidence, lawyers, compensation	lawyers, legal, investigation, solicitors, inquest, magistrates, hillsborough, court, lawyer, coroners, complaints, trial, witness, investigated, tribunals, disciplinary, allegations, alleged, inquiry, jury
Topic 78	support, help, take, taking, action, taken, measures, provide, steps, improve, encourage, supported, supporting, providing, tackle, department, reduce, assist, efforts, small	taking, support, help, steps, action, take, measures, encourage, supporting, assist, taken, improve, supported, provide, providing, supports, efforts, practical, package, assistance
Topic 79	businesses, business, industry, small, companies, manufacturing, uk, steel, industries, jobs, innovation, company, enterprise, constituency, british, many, firms, skills, trade, supply	steel, gambling, tata, businesses, manufacturing, medium-sized, smes, enterprises, innovation, betting, nissan, commerce, industries, start-ups, business, aerospace, beer, teesside, small, pub
Topic 80	committee, report, select, public, members, scrutiny, recommendations, government, independent, work, commission, role, chair, parliament, reports, committees, evidence, accountability, committee's, accounts	committee's, select, committee, scrutiny, committees, recommendations, recommendation, chairman, accountability, report, nao, panel, isc, pre-legislative, sir, chair, oversight, scrutinise, recommended, appointments
Topic 81	bbc, flood, radio, flooding, media, news, television, licence, risk, floods, environment, digital, insurance, charter, fee, coverage, cumbria, defences, resilience, programmes	bbc, flood, floods, flooding, radio, bbc's, cumbria, defences, broadcasters, broadcasting, s4c, flooded, television, re, ofcom, tv, charter, resilience, editorial, broadcaster
Topic 82	first, contribution, intervention, acknowledge, secondly, worth, reply, begin, plymouth, contribute, thirdly, south-west, field, quick, sake, devon, doncaster, mentioning, appreciated, pertinent	first, intervention, secondly, contribution, acknowledge, reply, begin, worth, thirdly, plymouth, quick, pertinent, sake, mentioning, devon, noting, south-west, contribute, field, intervening
Topic 83	work, pay, employment, working, workers, job, jobs, employers, wage, minimum, training, skills, staff, paid, national, hours, employees, new, contracts, opportunities	zero-hours, apprenticeships, employers, wage, workers, apprenticeship, employment, minimum, employees, employer, apprentices, job, part-time, unemployed, full-time, wages, low-paid, contracts, employed, reemploy
Topic 84	pleased, many, major, like, also, use, comment, given, much, recently, particularly, hope, place, throughout, still, able, used, know, fact, lack	pleased, comment, major, willingness, recently, throughout, breastfeeding, lobbied, along, like, enormous, lack, particularly, soon, urge, succeeded, supportive, produced, birth, similar

4.4.2 Full topic model summary - k0

A topic model with 84 topics, 81651 documents and a 119586 word dictionary.

Topic 1 Top Words:

Highest Prob: secretary, state, ministers, tell, home, department, confirm
FREX: secretary, state, confirm, ministers, state's, tell, explain
Lift: qatada, 1=yes, 1,631, 1120, 1135, 173-178, 1990s-tens
Score: secretary, state, confirm, home, ministers, state's, department

Topic 2 Top Words:

Highest Prob: clause, amendment, amendments, new, clauses, tabled, committee
FREX: nos, amendments, clause, clauses, schedule, tabled, amendment
Lift: 10.00, 1022, 108-111, 108a, 11-an, 112ten, 113three
Score: clause, amendment, amendments, nos, clauses, lords, provisions

Topic 3 Top Words:

Highest Prob: move, second, read, leave, line, agreed, reading
FREX: page, beg, read, insert, reading, agrees, move
Lift: 1,000,000, 22a, 4a1, 4b, 50b, 8a, paragraph5
Score: move, beg, lords, read, insert, page, reading

Topic 4 Top Words:

Highest Prob: housing, homes, private, social, affordable, accommodation, home
FREX: tenants, landlords, rented, homelessness, homeless, rents, tenancies
Lift: landlords, renters, rents, #19, 1,026, 1,083, 1,161
Score: housing, homes, rented, tenants, rent, landlords, affordable

Topic 5 Top Words:

Highest Prob: nhs, hospital, patients, staff, trust, hospitals, health
FREX: dentists, dental, dentistry, hospitals, hospital, nurses, pct
Lift: 2.24, 22,600, acos, addenbrookes, ambience's, anti-falls, appointable
Score: nhs, patients, hospital, dentists, hospitals, patient, dental

Topic 6 Top Words:

Highest Prob: make, sure, policy, statement, progress, plans, difference
FREX: make, statement, sure, progress, policy, difference, plans
Lift: 102938, 106583, 107305, 107883, 108542, 112172, 113404
Score: make, statement, progress, policy, sure, plans, difference

Topic 7 Top Words:

Highest Prob: can, ensure, welcome, work, aware, continue, done
FREX: ensure, aware, welcome, can, friend's, assure, ensuring
Lift: #ne, access-suggests, achieve-interruption, agency-so, anti-lobbying, area-will, beth's
Score: can, ensure, aware, welcome, assure, friend's, work

Topic 8 Top Words:

Highest Prob: issues, hope, however, must, consider, understand, matter
FREX: issues, consider, understand, matter, concerns, possible, certainly
Lift: beneficial-we, bill-albeit, billion-interruption, bullying-and, community-but, cyberbull
Score: issues, matter, consider, hope, raised, shall, concerns

Topic 9 Top Words:

Highest Prob: agree, making, absolutely, rather, completely, entirely, argument
FREX: agree, absolutely, making, completely, entirely, precisely, argument
Lift: 1998-it, 19992002, 200yd, about-creating, ages-have, apologise-the, behaviour-that
Score: agree, absolutely, making, completely, entirely, argument, rather

Topic 10 Top Words:

Highest Prob: community, communities, organisations, work, role, sector, voluntary
FREX: voluntary, community, partnership, organisations, play, communities, co-operative
Lift: allison's, b4box, communitybuilders, compacts, divi, elisabeth, futurebuilders
Score: community, communities, voluntary, sector, organisations, partnership, role

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## Topic 11 Top Words:
## Highest Prob: air, airport, indicated, airports, heathrow, aviation, noise
## FREX: aviation, flights, gatwick, dissent, airlines, runway, caa
## Lift: apd, caa, 0.45, 0315, 0345, 1.00, 11.63
## Score: airport, air, heathrow, airports, aviation, noise, indicated
## Topic 12 Top Words:
## Highest Prob: women, men, women's, pay, woman, gender, equal
## FREX: women, shortlists, gender, women's, all-women, men, female
## Lift: 1-breast-feed, 1,087, 1,574, 1.57, 102nd, 107.4, 11-even
## Score: women, women's, men, gender, girls, equality, female
## Topic 13 Top Words:
## Highest Prob: made, number, clear, impact, changes, recent, assessment
## FREX: made, recent, assessment, changes, impact, representations, discussions
## Lift: 104193, 104963, 105754, 114267, 115661, 118130, 119876
## Score: made, assessment, impact, changes, recent, discussions, number
## Topic 14 Top Words:
## Highest Prob: years, now, two, three, past, months, 10
## FREX: years, three, past, ago, months, two, four
## Lift: 103677, 38-1,140, basher, boasted-i, childcare-and, crucified, djodjo
## Score: years, two, months, three, ago, past, weeks
## Topic 15 Top Words:
## Highest Prob: whether, question, given, thank, ask, asked, put
## FREX: answer, question, ask, questions, thank, asked, grateful
## Lift: 150-million, 494th, 8k, 97755, 97800, 97801, age-discrimination
## Score: question, answer, thank, questions, whether, asked, ask
## Topic 16 Top Words:
## Highest Prob: post, office, petition, offices, closure, rural, royal
## FREX: petition, petitioners, sub-post, sub-postmasters, offices, mail, declares
## Lift: #450, 11,900, 7.12, ablewell, aesop's, aldred, annesley
## Score: post, petitioners, petition, offices, mail, declares, postal
## Topic 17 Top Words:
## Highest Prob: energy, climate, water, change, fuel, companies, bills
## FREX: energy, renewables, solar, ofgem, feed-in, electricity, carbon
## Lift: #2,500, #solar, 1,069, 1,105, 1,310, 1,345, 1,345-and
## Score: energy, carbon, fuel, climate, emissions, renewable, electricity
## Topic 18 Top Words:
## Highest Prob: constituency, constituents, many, great, proud, speech, represent
## FREX: maiden, constituency, hackney, mine, constituents, mp, swindon
## Lift: 1,365, 10-of, 10th-highest, 11,800, 12.22, 138th, 1711
## Score: constituency, constituents, maiden, hackney, town, swindon, labour
## Topic 19 Top Words:
## Highest Prob: want, go, really, wants, putting, ahead, prepared
## FREX: really, go, want, wants, prepared, ahead, putting
## Lift: 11,600-and, 3,000-i, about-by, achieve-but, achieved-but, achieved-is, acknowledging-int
## Score: go, want, really, wants, ahead, prepared, oh
## Topic 20 Top Words:
## Highest Prob: health, care, services, social, mental, service, need
## FREX: mental, health, care, suicide, commissioning, services, discharge
## Lift: 0.06, 1,395, 1,417, 104962, 12436, 131a, 158145
## Score: health, care, mental, services, social, service, suicide
## Topic 21 Top Words:
## Highest Prob: police, officers, crime, policing, home, force, fire
## FREX: constables, officers, policing, constable, police, soca, fire
## Lift: hmic, #22k, #29k, 1-2-3, 1,011, 1,027, 1,043

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Score: police, officers, crime, policing, forces, constable, neighbourhood

Topic 22 Top Words:

Highest Prob: marriage, church, ethnic, black, minority, faith, religious

FREX: gay, same-sex, humanist, marriage, holocaust, church, religious

Lift: anelka, buddhists, burslem, celebrants, cohabit, gurdwaras, hersh

Score: marriage, religious, holocaust, church, ethnic, gay, religion

Topic 23 Top Words:

Highest Prob: transport, bus, rail, services, travel, train, line

FREX: bus, fares, buses, concessionary, franchising, railtrack, fare

Lift: 10.03, 12-car, 125s, 15.15, 33.6, 416,000, adac

Score: rail, bus, transport, fares, passengers, trains, buses

Topic 24 Top Words:

Highest Prob: smoking, ban, charities, animals, food, charity, health

FREX: tobacco, fur, mink, circuses, sunbeds, sunbed, snares

Lift: coursing, snares, #0.5, 0.037, 0.044, 027, 1,000-almost

Score: smoking, animals, tobacco, ban, animal, fireworks, fur

Topic 25 Top Words:

Highest Prob: home, immigration, uk, country, asylum, office, system

FREX: immigration, asylum, seekers, passports, nationality, migration, passport

Lift: immigration, seekers, #35,000, 0.025, 1,116, 1,256, 10,410

Score: immigration, asylum, refugees, seekers, migration, passport, nationals

Topic 26 Top Words:

Highest Prob: said, us, even, let, enough, wrong, simply

FREX: wrong, let, thought, saying, anything, seems, though

Lift: 2-can, 2-or, 5,000-if, am-if, analysis-this, antoine, anybody-need

Score: wrong, us, even, said, let, saying, told

Topic 27 Top Words:

Highest Prob: get, know, think, say, much, see, going

FREX: get, going, things, think, something, lot, talking

Lift: 6,000-they, 70.70, allowance-have, assembly-but, barrels-i, britons-20, coal-to

Score: get, going, think, things, know, say, lot

Topic 28 Top Words:

Highest Prob: debt, banks, bank, credit, financial, fees, pay

FREX: payday, lending, loans, farepak, loan, banks, lenders

Lift: overdraft, payday, 0.21, 0.33, 0.84, 1,021, 1,189

Score: banks, debt, bank, payday, loan, loans, lending

Topic 29 Top Words:

Highest Prob: million, funding, money, cuts, increase, extra, year

FREX: funding, million, grant, formula, spending, extra, expenditure

Lift: #47, #500,000, 0.41, 000-to, 1,608, 1,808, 1,838

Score: funding, million, cuts, money, billion, spending, budget

Topic 30 Top Words:

Highest Prob: year, since, last, report, figures, number, said

FREX: march, january, october, official, 2011, figures, november

Lift: may-second, reportscm, rethishkumar, vol, 01, 1,033, 1,124,818

Score: year, last, figures, report, official, since, april

Topic 31 Top Words:

Highest Prob: abuse, children, protection, child, sexual, vulnerable, trafficking

FREX: pornography, barring, crb, trafficked, abuse, grooming, trafficking

Lift: crb, @mandatenow, 1,746, 12,992, 12j, 135wh, 16-only

Score: abuse, sexual, trafficking, children, child, sex, trafficked

Topic 32 Top Words:

Highest Prob: act, person, offence, order, law, orders, powers

FREX: orders, offence, reasonable, person, tpims, proportionate, surveillance

Lift: 1,125, 10-application, 10-duty, 106b, 106c, 106d, 11-failure
 ## Score: offence, orders, offences, person, terrorism, criminal, powers
 ## Topic 33 Top Words:
 ## Highest Prob: sport, football, club, clubs, sports, games, event
 ## FREX: touts, games, olympic, football, copyright, olympics, sport
 ## Lift: abebrese, aquatics, athletes, atterbury, bpa, cafeteria, friedrich
 ## Score: sport, tickets, football, sports, clubs, games, olympic
 ## Topic 34 Top Words:
 ## Highest Prob: good, best, bad, called, practice, tories, examples
 ## FREX: good, bad, tories, luton, ideas, examples, 21st
 ## Lift: 070, 1,000-by, 1,126, 158.8, 1676, 18,000-plus, 1979-80
 ## Score: good, tories, bad, luton, practice, called, best
 ## Topic 35 Top Words:
 ## Highest Prob: parliament, scotland, scottish, united, kingdom, devolution, uk
 ## FREX: scotland, scottish, snp, scotland's, holyrood, calman, vellum
 ## Lift: acoba, alloway, archival, auchinleck, bonis, calman, circumstantial
 ## Score: scottish, scotland, parliament, devolution, snp, kingdom, devolved
 ## Topic 36 Top Words:
 ## Highest Prob: bristol, arts, national, great, heritage, many, area
 ## FREX: museum, arts, gospels, morecambe, bristol, heritage, museums
 ## Lift: archaeology, lindisfarne, 1,314, 1,468, 1,983, 1.41, 114864
 ## Score: arts, museum, bristol, heritage, tourism, engineering, countryside
 ## Topic 37 Top Words:
 ## Highest Prob: research, medical, science, use, stem, human, health
 ## FREX: embryos, abortion, hepatitis, cloning, organs, abortions, embryonic
 ## Lift: anonymisation, blar, henna, hfea, look-back, nihr, o'malley
 ## Score: embryos, research, tissue, cell, cloning, abortion, cells
 ## Topic 38 Top Words:
 ## Highest Prob: vote, political, election, parties, elected, parliament, democracy
 ## FREX: electoral, vote, voting, elections, voters, votes, democracy
 ## Lift: 1,294, 1,516,000, 121543, 128,000, 146,567, 149,615, 16-just
 ## Score: vote, electoral, elections, democracy, political, voting, referendum
 ## Topic 39 Top Words:
 ## Highest Prob: economy, economic, jobs, growth, investment, chancellor, budget
 ## FREX: recession, economy, growth, productivity, deficit, obr, gdp
 ## Lift: a-plus, face-the, fitch, forecasters, olivier, peashooter, second-round
 ## Score: economy, jobs, growth, unemployment, chancellor, investment, economic
 ## Topic 40 Top Words:
 ## Highest Prob: international, countries, world, development, aid, developing, uk
 ## FREX: zimbabwe, burma, dfid, congo, burmese, sri, cancan
 ## Lift: cancan, congo, lars, rohingya, suu, #640, 0.26
 ## Score: countries, international, un, africa, sri, sierra, zimbabwe
 ## Topic 41 Top Words:
 ## Highest Prob: group, needs, special, learning, training, disabled, all-party
 ## FREX: autism, sen, deaf, autistic, dyslexia, disabilities, special
 ## Lift: ilas, sen2, autistic, deaf, sen, 1,204, 1,333,430
 ## Score: autism, sen, disability, disabled, learning, disabilities, all-party
 ## Topic 42 Top Words:
 ## Highest Prob: defence, forces, armed, service, personnel, military, army
 ## FREX: veterans, mod, naval, hms, reservists, submarines, regiment
 ## Lift: 45s, adventurers, asia-pacific, canberra, casd, cimic, cnd
 ## Score: armed, defence, forces, military, veterans, personnel, afghanistan
 ## Topic 43 Top Words:
 ## Highest Prob: government, government's, labour, country, previous, policies, yet

FREX: government, government's, previous, failed, coalition, promise, labour's
 ## Lift: 1071, 1945-51, 2010-interruption, 2010-yields, 2018-fully, 218.2, 21s-not
 ## Score: government, labour, government's, crisis, tory, previous, coalition
 ## Topic 44 Top Words:
 ## Highest Prob: information, available, guidance, data, advice, details, arrangements
 ## FREX: information, data, details, guidance, accurate, issued, officials
 ## Lift: 2003-morecambe, 22-year-old's, 2b1, apn, appropriations-in-aid, baythe, biographic
 ## Score: information, data, guidance, advice, available, census, registration
 ## Topic 45 Top Words:
 ## Highest Prob: violence, domestic, victims, justice, prison, rape, criminal
 ## FREX: prison, probation, reoffending, prisons, rape, sentences, prisoners
 ## Lift: fss, hmp, #7, #9, 0.48, 1,145, 10,000-of
 ## Score: violence, prison, rape, victims, domestic, offenders, prisons
 ## Topic 46 Top Words:
 ## Highest Prob: food, farmers, industry, environment, rural, oil, waste
 ## FREX: fisheries, fishermen, cod, visteon, mmo, farmers, fishing
 ## Lift: 0.8p, 0157, 1-tonne, 1,004, 1,129, 1.88, 1.98
 ## Score: farmers, food, marine, oil, fishing, fisheries, fishermen
 ## Topic 47 Top Words:
 ## Highest Prob: security, peace, foreign, war, conflict, threat, syria
 ## FREX: israel, palestinian, israeli, gaza, yemen, daesh, palestinians
 ## Lift: airlifts, airstrikes, al-mansour, alabed, aleppo, alevi, amona
 ## Score: syria, israel, palestinian, israeli, iraq, civilians, gaza
 ## Topic 48 Top Words:
 ## Highest Prob: london, city, north, north-east, hull, liverpool, country
 ## FREX: hull, city, north-east, mayor, london, newcastle, liverpool
 ## Lift: richmondshire, xcase, #356, #38, 1,018, 1,386, 1,507
 ## Score: london, city, hull, north-east, liverpool, mayor, yorkshire
 ## Topic 49 Top Words:
 ## Highest Prob: children, child, parents, families, care, children's, family
 ## FREX: csa, child's, adopters, lone, parents, parent, children's
 ## Lift: bont, creche, creches, daycare, demand-side-only, dummies, ehcps
 ## Score: children, child, parents, care, children's, families, adoption
 ## Topic 50 Top Words:
 ## Highest Prob: behaviour, crime, antisocial, alcohol, drugs, drug, problem
 ## FREX: alcohol, antisocial, asbos, alcohol-related, drinking, binge, misuse
 ## Lift: 1,113, 199,000, 664, acpo's, adz, airsoft, alleygator
 ## Score: antisocial, alcohol, crime, behaviour, drug, drugs, cannabis
 ## Topic 51 Top Words:
 ## Highest Prob: scheme, pension, pensions, pensioners, schemes, insurance, savings
 ## FREX: pension, pensioners, retirement, pensions, scheme, pensioner, annuity
 ## Lift: 13a, 92.15, a-day, aggregators, amoco, aps, avc
 ## Score: pension, pensioners, scheme, pensions, retirement, insurance, savings
 ## Topic 52 Top Words:
 ## Highest Prob: public, proposals, consultation, new, service, access, paper
 ## FREX: proposals, consultation, paper, white, document, broadband, electronic
 ## Lift: 109648, 111535, 113697, 114061, 119621, 126118, 127924
 ## Score: proposals, consultation, public, paper, service, white, access
 ## Topic 53 Top Words:
 ## Highest Prob: planning, land, development, new, building, site, sites
 ## FREX: brownfield, planning, leaseholders, eco-towns, land, developers, leasehold
 ## Lift: 44a, addingham, bandstand, brickmaking, brs-bids, commonhold, commutable
 ## Score: planning, land, sites, site, leaseholders, developers, brownfield
 ## Topic 54 Top Words:

Highest Prob: members, opposition, conservative, party, said, heard, hear
 ## FREX: conservative, liberal, democrats, opposition, conservatives, benches, democrat
 ## Lift: 11,511, 15-years, 2million, 350bn, 42,000-a, 65-i, 74p
 ## Score: conservative, opposition, party, members, liberal, conservatives, democrats
 ## Topic 55 Top Words:
 ## Highest Prob: benefit, work, people, benefits, disabled, allowance, system
 ## FREX: esa, dla, atos, claimants, incapacity, dwp, allowance
 ## Lift: dla, esa, #400, 0300, 0°, 1-to-1, 1,052
 ## Score: disabled, allowance, disability, claimants, benefit, credit, welfare
 ## Topic 56 Top Words:
 ## Highest Prob: case, decision, process, decisions, cases, evidence, taken
 ## FREX: appeal, decision, judgment, decisions, case, judicial, decide
 ## Lift: 1,220, 1,237, 114042, 120946, 131294, 15.45, 1501
 ## Score: decision, case, judicial, appeal, cases, decisions, process
 ## Topic 57 Top Words:
 ## Highest Prob: house, debate, may, order, mr, speaker, deputy
 ## FREX: leader, speaker, deputy, house, apologise, madam, motion
 ## Lift: 10,000-signature, 11.40, 1105, 114063, 1170, 12.26, 12.40
 ## Score: house, speaker, leader, debate, mr, deputy, motion
 ## Topic 58 Top Words:
 ## Highest Prob: one, time, last, long, week, speak, later
 ## FREX: one, time, long, call, week, short, later
 ## Lift: 4.27, 6.47pm, business-on, cities-but, concerned-hon, contentment, directly-we
 ## Score: one, time, last, week, long, speak, later
 ## Topic 59 Top Words:
 ## Highest Prob: important, need, point, issue, also, different, part
 ## FREX: important, point, different, issue, makes, extremely, points
 ## Lift: aquaplaning, authorities-wrongly, available-not, better-grip, business-of, campaigns-by,
 ## Score: important, point, need, issue, makes, different, points
 ## Topic 60 Top Words:
 ## Highest Prob: poverty, poor, social, low, living, average, poorest
 ## FREX: poverty, deprivation, poorest, poor, poorer, inequality, inequalities
 ## Lift: after-housing-costs, attachment-free, before-housing-costs, harker, seacroft, 0207, 1,05
 ## Score: poverty, poorest, inequalities, inequality, incomes, deprivation, income
 ## Topic 61 Top Words:
 ## Highest Prob: bill, legislation, act, law, provisions, powers, introduced
 ## FREX: bill, legislation, bill's, passage, provisions, legislative, draft
 ## Lift: 1431, 1865, 2006-which, 6-7, 61094, 647, add-selection
 ## Score: bill, legislation, provisions, powers, bill's, law, regulations
 ## Topic 62 Top Words:
 ## Highest Prob: tax, rate, families, pay, income, credits, chancellor
 ## FREX: tax, 50p, vat, credits, taxes, avoidance, taxation
 ## Lift: anti-tax, cgt, raiser, tax-avoidance, #127, #3.5, #840
 ## Score: tax, credits, vat, income, avoidance, chancellor, hmrc
 ## Topic 63 Top Words:
 ## Highest Prob: people, young, many, lives, people's, life, age
 ## FREX: young, people, people's, youth, lives, 16, age
 ## Lift: 1034, 1053, 15-interruption, 16-should, 17-year-olds-interruption, 17-years-old, 18-it
 ## Score: people, young, youth, age, people's, lives, older
 ## Topic 64 Top Words:
 ## Highest Prob: programme, strategy, department, national, plan, safety, key
 ## FREX: programme, strategy, pilot, flu, performance, priority, programmes
 ## Lift: avian, influenza, #62, 0.09, 0.16, 1,705, 106249
 ## Score: programme, strategy, safety, programmes, vaccine, flu, department

Topic 65 Top Words:
 ## Highest Prob: heart, trade, unions, union, stroke, disease, slough
 ## FREX: mesothelioma, cpr, heart, stroke, asbestos, cardiomyopathy, slough
 ## Lift: 124,665, abolitionists, arrhythmogenic, black-outs, bowen, cardiopulmonary, cardioverter
 ## Score: unions, trade, stroke, heart, union, disease, slough

Topic 66 Top Words:
 ## Highest Prob: treatment, cancer, patients, screening, clinical, condition, disease
 ## FREX: prostate, cervical, endometriosis, breast, screening, cancer, treatment
 ## Lift: her2, endometriosis, fibrosis, herceptin, hpv, radiotherapy, @cfaware
 ## Score: cancer, treatment, patients, screening, breast, clinical, diagnosis

Topic 67 Top Words:
 ## Highest Prob: local, authorities, council, authority, councils, area, areas
 ## FREX: local, authorities, councils, authority, councillors, council, county
 ## Lift: banham, central-local, laa, lsp, place-shaping, sev, un-ring-fenced
 ## Score: local, authorities, councils, authority, council, county, councillors

Topic 68 Top Words:
 ## Highest Prob: rights, wales, human, northern, ireland, commission, welsh
 ## FREX: ireland, welsh, rights, assembly, wales, convention, human
 ## Lift: cre, guatemalan, meathygiene, melding, securitynorthern, 1,099, 1,748
 ## Score: rights, wales, human, welsh, assembly, ireland, northern

Topic 69 Top Words:
 ## Highest Prob: east, st, south, friends, heard, west, birmingham
 ## FREX: helier, cooper, bromley, stuart, croydon, ealing, castlefordyvette
 ## Lift: 0.37, 0.66, 1,000-square-feet, 1,131, 12.70, 130b, 15.18
 ## Score: helier, st, east, sunderland, ealing, worthing, bromley

Topic 70 Top Words:
 ## Highest Prob: member, members, debate, speech, also, spoke, mentioned
 ## FREX: member, spoke, remarks, talked, thoughtful, eloquently, pleasure
 ## Lift: 1028, 1993-more, 31.2, business-let, career-which, cases-a, chamber-pointed
 ## Score: member, members, debate, spoke, speech, north, talked

Topic 71 Top Words:
 ## Highest Prob: european, eu, union, uk, europe, states, british
 ## FREX: treaty, lisbon, european, eu, accession, brexit, euro
 ## Lift: 1-2, 1-of, 1,057, 1.14, 10-month, 10249, 10516
 ## Score: eu, european, treaty, union, europe, negotiations, brexit

Topic 72 Top Words:
 ## Highest Prob: carers, family, constituent, told, families, life, home
 ## FREX: carers, constituent, dementia, caring, mrs, husband, son
 ## Lift: 62-year-old, brechin, gravestones, haemophiliac, jayden's, mnd, stepfather
 ## Score: carers, caring, constituent, dementia, carer, family, mother

Topic 73 Top Words:
 ## Highest Prob: schools, education, school, teachers, students, university, children
 ## FREX: schools, teachers, academies, grammar, fe, gcse, pupils
 ## Lift: apostrophe, headteachers, academisation, gcse, grammar, school's, #8,000
 ## Score: schools, school, education, teachers, pupils, students, teaching

Topic 74 Top Words:
 ## Highest Prob: regional, development, road, investment, transport, new, economic
 ## FREX: hs2, regional, rdas, high-speed, rda, crossrail, regeneration
 ## Lift: #145, 1-very, 10-is, 109g, 1185, 12375, 128406
 ## Score: regional, transport, regeneration, hs2, infrastructure, development, roads

Topic 75 Top Words:
 ## Highest Prob: company, companies, financial, regulation, standards, competition, regulatory
 ## FREX: policyholders, fsa, regulatory, corporate, ombudsman, regulators, liabilities
 ## Lift: #45, 1-on, 1,699,137, 1003, 1174, 1297, 130-with

```

##      Score: fsa, regulatory, company, regulation, companies, consumers, competition
## Topic 76 Top Words:
##      Highest Prob: course, indeed, lady, meet, happy, note, glad
##      FREX: lady, course, indeed, happy, note, glad, lady's
##      Lift: about-who, betws, chaplaincies, constituents-members, course-politics, ditch-a-policy-a-
##      Score: lady, course, indeed, happy, meet, glad, note
## Topic 77 Top Words:
##      Highest Prob: legal, court, justice, courts, inquiry, investigation, cases
##      FREX: lawyers, legal, investigation, solicitors, inquest, magistrates, hillsborough
##      Lift: asphyxia, blagging, blameworthiness, cairns's, carlyle-clarke's, ccrc's, defamed
##      Score: court, legal, courts, justice, investigation, magistrates, inquiry
## Topic 78 Top Words:
##      Highest Prob: support, help, take, taking, action, taken, measures
##      FREX: taking, support, help, steps, action, take, measures
##      Lift: 101997, 103264, 103684, 105939, 107320, 113698, 117890
##      Score: support, help, steps, taking, action, measures, take
## Topic 79 Top Words:
##      Highest Prob: businesses, business, industry, small, companies, manufacturing, uk
##      FREX: steel, gambling, tata, businesses, manufacturing, medium-sized, smes
##      Lift: budgen, killie, s's, steel, #12.5, #140,000, #23
##      Score: businesses, industry, business, manufacturing, steel, companies, small
## Topic 80 Top Words:
##      Highest Prob: committee, report, select, public, members, scrutiny, recommendations
##      FREX: committee's, select, committee, scrutiny, committees, recommendations, recommendation
##      Lift: isc's, post-legislative, 1,924, 1080, 109657, 109658, 1240s
##      Score: committee, select, report, scrutiny, committees, recommendations, committee's
## Topic 81 Top Words:
##      Highest Prob: bbc, flood, radio, flooding, media, news, television
##      FREX: bbc, flood, floods, flooding, radio, bbc's, cumbria
##      Lift: landslips, one-in-200-year, reithian, bellwin, #bbcdiversity, 1,000-year, 1,800-strong
##      Score: bbc, flood, flooding, floods, radio, defences, digital
## Topic 82 Top Words:
##      Highest Prob: first, contribution, intervention, acknowledge, secondly, worth, reply
##      FREX: first, intervention, secondly, contribution, acknowledge, reply, begin
##      Lift: @daisydumble, @percyblakeney63, abba, available-probably, avenger, average-a, bagging
##      Score: first, contribution, plymouth, intervention, reply, secondly, acknowledge
## Topic 83 Top Words:
##      Highest Prob: work, pay, employment, working, workers, job, jobs
##      FREX: zero-hours, apprenticeships, employers, wage, workers, apprenticeship, employment
##      Lift: zero-hours, 1,030, 1,308, 1,650, 1,735, 1,803, 10-hours
##      Score: wage, employers, employment, workers, jobs, apprenticeships, work
## Topic 84 Top Words:
##      Highest Prob: pleased, many, major, like, also, use, comment
##      FREX: pleased, comment, major, willingness, recently, throughout, breastfeeding
##      Lift: height-variable, available-most, better-at, board-young, breastmilk, buggies-could, cons
##      Score: pleased, breastfeeding, comment, many, major, constituents, nsf

```

4.4.3 Full topic model estimate summary - k0

```

##
## Call:
## estimateEffect(formula = 1:84 ~ short_list, stmobj = topic_model_k0,
##      metadata = lab_corpus_fem_stm$meta, uncertainty = "Global")

```

```

##
##
## Topic 1:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0128879  0.0002388   53.97 <0.0000000000000002 ***
## short_listTRUE 0.0048966  0.0002878   17.01 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 2:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0147970  0.0004205   35.189 < 0.0000000000000002 ***
## short_listTRUE -0.0018899  0.0005098   -3.707      0.00021 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0082674  0.0002435   33.954 < 0.0000000000000002 ***
## short_listTRUE -0.0012094  0.0003091   -3.913      0.0000912 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0117249  0.0004612   25.423 < 0.0000000000000002 ***
## short_listTRUE 0.0030551  0.0005773    5.292      0.000000121 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 5:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0237311  0.0006317   37.566 <0.0000000000000002 ***
## short_listTRUE -0.0069901  0.0007786   -8.978 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 6:
##

```

```

## Coefficients:
##               Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.00869710 0.00009726  89.423 <0.0000000000000002 ***
## short_listTRUE 0.00023612 0.00012214   1.933    0.0532 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##               Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0152453  0.0001136  134.22 <0.0000000000000002 ***
## short_listTRUE -0.0019480  0.0001392  -13.99 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 8:
##
## Coefficients:
##               Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0295333  0.0002204  134.03 <0.0000000000000002 ***
## short_listTRUE -0.0057613  0.0002623  -21.96 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 9:
##
## Coefficients:
##               Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.00668167 0.00006662 100.299 <0.0000000000000002 ***
## short_listTRUE 0.00022618 0.00007567   2.989    0.0028 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##               Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0196173  0.0003394   57.81 <0.0000000000000002 ***
## short_listTRUE -0.0051505  0.0004210  -12.23 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
##               Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0055820  0.0002860   19.52 <0.0000000000000002 ***
## short_listTRUE 0.0006503  0.0003654    1.78    0.0751 .

```



```

## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 12:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0110052  0.0003898  28.230 <0.0000000000000002 ***
## short_listTRUE 0.0001758  0.0004922   0.357      0.721
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0104934  0.0001339  78.351 < 0.0000000000000002 ***
## short_listTRUE 0.0013407  0.0001637   8.188 0.000000000000000268 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.01296551  0.00012510 103.638 <0.0000000000000002 ***
## short_listTRUE -0.00006996  0.00015830  -0.442      0.659
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0104991  0.0001083  96.933 < 0.0000000000000002 ***
## short_listTRUE 0.0010409  0.0001364   7.632  0.00000000000000233 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 16:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0091936  0.0003704  24.822 <0.0000000000000002 ***
## short_listTRUE 0.0002083  0.0004366   0.477      0.633
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##

```

```

## Topic 17:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0154864  0.0004375  35.396 < 0.0000000000000002 ***
## short_listTRUE -0.0032954  0.0005568  -5.918      0.00000000327 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0079826  0.0002059  38.78 <0.0000000000000002 ***
## short_listTRUE 0.0036801  0.0002584  14.24 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 19:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.00579759  0.00007843  73.925 < 0.0000000000000002 ***
## short_listTRUE -0.00029355  0.00008349  -3.516      0.000438 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0137650  0.0003555  38.721 < 0.0000000000000002 ***
## short_listTRUE -0.0012415  0.0004335  -2.864      0.00419 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0149443  0.0004880  30.625 < 0.0000000000000002 ***
## short_listTRUE -0.0036366  0.0005923  -6.139      0.000000000832 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 22:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)

```

```

## (Intercept)    0.0084321  0.0003444  24.487 <0.0000000000000002 ***
## short_listTRUE 0.0009344  0.0004294   2.176          0.0296 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 23:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0107287  0.0004871  22.027 < 0.0000000000000002 ***
## short_listTRUE 0.0029620  0.0005669   5.225      0.000000175 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0068237  0.0003497  19.515 < 0.0000000000000002 ***
## short_listTRUE 0.0031732  0.0004608   6.886      0.00000000000579 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 25:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0124772  0.0004087  30.531 < 0.0000000000000002 ***
## short_listTRUE -0.0019736  0.0005224  -3.778      0.000158 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0171457  0.0001819  94.24 <0.0000000000000002 ***
## short_listTRUE 0.0025471  0.0002246  11.34 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0237688  0.0001801 131.953 < 0.0000000000000002 ***
## short_listTRUE 0.0013294  0.0002265   5.869      0.0000000044 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

##
##
## Topic 28:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0091614  0.0003764  24.340 < 0.0000000000000002 ***
## short_listTRUE 0.0039054  0.0004802   8.132 0.000000000000000428 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0185899  0.0003319  56.008 <0.0000000000000002 ***
## short_listTRUE -0.0001861  0.0003937  -0.473      0.636
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 30:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0162129  0.0002572  63.046 <0.0000000000000002 ***
## short_listTRUE 0.0007083  0.0003034   2.335      0.0196 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 31:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0097946  0.0003472  28.208 < 0.0000000000000002 ***
## short_listTRUE -0.0012523  0.0004211  -2.974      0.00294 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 32:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0175131  0.0004029  43.47 <0.0000000000000002 ***
## short_listTRUE -0.0075562  0.0004415  -17.12 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 33:
##

```

```

## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0047982  0.0002605  18.419 < 0.0000000000000002 ***
## short_listTRUE 0.0022766  0.0003204   7.105    0.000000000000121 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 34:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.00528774  0.00009125  57.946 <0.0000000000000002 ***
## short_listTRUE -0.00014490  0.00010982  -1.319      0.187
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 35:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0083656  0.0003087   27.10 <0.0000000000000002 ***
## short_listTRUE 0.0001019  0.0003920    0.26      0.795
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 36:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0078616  0.0003005   26.161 <0.0000000000000002 ***
## short_listTRUE 0.0003457  0.0003916    0.883      0.377
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 37:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0102571  0.0003878   26.451 < 0.0000000000000002 ***
## short_listTRUE -0.0034037  0.0004576  -7.438    0.000000000000104 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 38:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0098004  0.0003748   26.148 < 0.0000000000000002 ***
## short_listTRUE 0.0030297  0.0004478    6.765    0.00000000000134 ***

```

```

## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 39:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0148468  0.0003782  39.254 <0.0000000000000002 ***
## short_listTRUE 0.0010644  0.0004595   2.316      0.0205 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 40:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0172037  0.0004968  34.626 < 0.0000000000000002 ***
## short_listTRUE -0.0045073  0.0005685  -7.928  0.00000000000000225 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 41:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0068713  0.0002459  27.942 < 0.0000000000000002 ***
## short_listTRUE 0.0018029  0.0003209   5.618      0.0000000194 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 42:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0086577  0.0004153  20.846 < 0.0000000000000002 ***
## short_listTRUE 0.0027363  0.0005279   5.183      0.0000000219 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 43:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0137459  0.0001710   80.4 <0.0000000000000002 ***
## short_listTRUE 0.0034644  0.0002264   15.3 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##

```

```

## Topic 44:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0148543  0.0002955  50.269 < 0.0000000000000002 ***
## short_listTRUE -0.0022491  0.0003155  -7.129    0.00000000000102 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 45:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0141144  0.0004702  30.017 < 0.0000000000000002 ***
## short_listTRUE -0.0019731  0.0005716  -3.452    0.000558 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 46:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0081245  0.0003814  21.300 < 0.0000000000000002 ***
## short_listTRUE 0.0024995  0.0005179   4.826    0.0000014 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 47:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0137924  0.0005335  25.851 < 0.0000000000000002 ***
## short_listTRUE 0.0023396  0.0006418   3.646    0.000267 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 48:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0068252  0.0002316  29.47 <0.0000000000000002 ***
## short_listTRUE 0.0045035  0.0003279  13.74 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 49:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)

```

```

## (Intercept)      0.0128918  0.0003693  34.907 <0.0000000000000002 ***
## short_listTRUE  0.0006911  0.0004784   1.445          0.149
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 50:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    0.0134236  0.0004206  31.919 < 0.0000000000000002 ***
## short_listTRUE -0.0026344  0.0004881  -5.398    0.0000000677 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 51:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    0.0115997  0.0003911  29.659 < 0.0000000000000002 ***
## short_listTRUE  0.0015237  0.0005032   3.028    0.00246 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 52:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    0.0121924  0.0002033  59.971 <0.0000000000000002 ***
## short_listTRUE -0.0021462  0.0002393  -8.968 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 53:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    0.0107998  0.0003190  33.856 < 0.0000000000000002 ***
## short_listTRUE -0.0027898  0.0003841  -7.262    0.000000000000384 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 54:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    0.0153573  0.0002299  66.790 <0.0000000000000002 ***
## short_listTRUE  0.0003721  0.0002809   1.324    0.185
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```



```

##
##
## Topic 55:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0081931  0.0003580   22.88 <0.0000000000000002 ***
## short_listTRUE 0.0089449  0.0004563   19.60 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 56:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0171047  0.0002400   71.27 <0.0000000000000002 ***
## short_listTRUE -0.0060464  0.0002946  -20.52 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 57:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0134756  0.0002526   53.34 <0.0000000000000002 ***
## short_listTRUE 0.0045549  0.0003294   13.83 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 58:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.00871694 0.00006347  137.33 <0.0000000000000002 ***
## short_listTRUE 0.00103172 0.00008206   12.57 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 59:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0189656  0.0001357  139.77 <0.0000000000000002 ***
## short_listTRUE -0.0038755  0.0001703  -22.75 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 60:
##

```

```

## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0111282  0.0003260  34.136 < 0.0000000000000002 ***
## short_listTRUE 0.0021727  0.0004286   5.069    0.000000401 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 61:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0153738  0.0002708  56.764 < 0.0000000000000002 ***
## short_listTRUE -0.0013690  0.0003494  -3.918    0.0000893 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 62:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0140782  0.0004625  30.438 <0.0000000000000002 ***
## short_listTRUE 0.0059464  0.0006550   9.078 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 63:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.01290439  0.00016958  76.095 <0.0000000000000002 ***
## short_listTRUE -0.00009559  0.00020631  -0.463    0.643
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 64:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0146834  0.0002490  58.98 <0.0000000000000002 ***
## short_listTRUE -0.0035576  0.0002926  -12.16 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 65:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0051122  0.0002211  23.117 <0.0000000000000002 ***
## short_listTRUE 0.0005204  0.0002705   1.924    0.0543 .

```

```

## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 66:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0095127  0.0003485  27.293 < 0.0000000000000002 ***
## short_listTRUE -0.0022159  0.0004253  -5.211      0.000000188 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 67:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0157420  0.0002897  54.33 <0.0000000000000002 ***
## short_listTRUE -0.0038403  0.0003589 -10.70 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 68:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0079539  0.0002804  28.363 < 0.0000000000000002 ***
## short_listTRUE 0.0013677  0.0003490   3.919      0.000089 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 69:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0051646  0.0002128  24.265 < 0.0000000000000002 ***
## short_listTRUE 0.0017686  0.0002807   6.301      0.000000000298 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 70:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0103989  0.0001811  57.428 <0.0000000000000002 ***
## short_listTRUE 0.0002382  0.0002251   1.058      0.29
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##

```

```

## Topic 71:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0171734  0.0004689  36.623 < 0.0000000000000002 ***
## short_listTRUE -0.0033318  0.0005490  -6.069      0.00000000129 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 72:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0084227  0.0003766  22.36 <0.0000000000000002 ***
## short_listTRUE 0.0050686  0.0004627  10.95 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 73:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0166791  0.0005153  32.365 < 0.0000000000000002 ***
## short_listTRUE 0.0031370  0.0006352   4.939      0.000000787 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 74:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0121465  0.0003750  32.390 < 0.0000000000000002 ***
## short_listTRUE -0.0012747  0.0004788  -2.662      0.00776 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 75:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   0.0161745  0.0003987  40.57 <0.0000000000000002 ***
## short_listTRUE -0.0058975  0.0004633  -12.73 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 76:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)

```

```

## (Intercept)      0.00394178  0.00003248  121.35 <0.0000000000000002 ***
## short_listTRUE -0.00054651  0.00003804  -14.37 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 77:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    0.0140378  0.0003436  40.854 <0.0000000000000002 ***
## short_listTRUE -0.0037157  0.0004052  -9.169 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 78:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    0.0117276  0.0001137 103.174 <0.0000000000000002 ***
## short_listTRUE -0.0011799  0.0001401  -8.424 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 79:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    0.0128036  0.0004366  29.329 <0.0000000000000002 ***
## short_listTRUE 0.0009726  0.0005194   1.873    0.0611 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 80:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    0.0136252  0.0003409  39.970 <0.0000000000000002 ***
## short_listTRUE 0.0015537  0.0004324   3.593    0.000327 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 81:
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    0.0035181  0.0002157  16.31 <0.0000000000000002 ***
## short_listTRUE 0.0030867  0.0002648  11.65 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

##
##
## Topic 82:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.00308509 0.00002976 103.650 <0.0000000000000002 ***
## short_listTRUE 0.00010062 0.00003640   2.765      0.0057 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 83:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.0147560 0.0003376  43.715 <0.0000000000000002 ***
## short_listTRUE 0.0009659 0.0004470   2.161      0.0307 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 84:
##
## Coefficients:
##           Estimate Std. Error t value      Pr(>|t|)
## (Intercept)  0.002166191 0.000020535 105.49 <0.0000000000000002 ***
## short_listTRUE 0.000001895 0.000023609   0.08      0.936
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

4.5 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 21: 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 ,
150 per cent . two years ago .	my constituents	if such banking
Another of	my constituency	has advised me of an application
already begun , for example just	my constituency	for an 85 per
over the border from	my constituency	in the constituency of my hon .
in which Cornish children study .	my constituency	Friend the Member
Three secondary schools in	my constituents	will be located on the same site ,
Manchester has been doing a	my constituents	and one
major infrastructure project , and	my constituents	are at the end of their tether
patient at the BRI , and Airedale	my constituency	about the lack
hospital is in	my constituency	. The hon . Member for South
, but the reality is there to be	my constituency	CambridgeshireMr . Lansley
seen in	my constituency	. On Saturday I met a delegation
		of workers from

Table 21: A random sample of KWIC's (*continued*)

Pre	Keyword	Post
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 Alder car community school in	my constituency	and its staff and pupils ? The percentage of pupils
n " , " 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 . \ n
. 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 . \ n
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 BuckinghamJohn Bercow
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

Table 21: A random sample of KWIC's (*continued*)

Pre	Keyword	Post
, 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	my constituency	to find a local solution . These reforms coincide with
north-east Derbyshire and dentists in		
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
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	. \ n " , " In February I visited
n " , " 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

Table 21: A random sample of KWIC's (*continued*)

Pre	Keyword	Post
in child benefit , which will help 13,800 families in	my constituency	. My real reason for tabling the question is to
for Finchley and Golders GreenMike 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
again have a university .	my constituency	Manchester is
However , Nene college in		hopes to change all that , and I
Enforcement Campaign-in	my constituent	support strongly
Cardiff , and particularly to the work of		, 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 .
in particular from the	My constituency	Friend the Member
circumstances of students in		contains both a higher education
Northampton .		and a further education college
the marine Bill on the grounds of	my constituents	, because , like the hon . Lady , I
its irrelevance to		
deepest concern for the families	my constituency	neighbours that of my hon .
involved , especially given that		Friend the Member for
services can expand on the slow	my constituents	benefit from the west coast main
line so that all		line upgrade ?
rehabilitation . \ n " , " The	my constituency	have been horrified by those
people of		cases , and it is
Labour Government we have	my constituency	the number of people claiming
achieved a tremendous amount .		jobseeker's allowance has almost
In		halved
they complain ? Where will the	My constituents	very much value the highly
local accountability go ?		accessible local service that they
n " , " Since helping the Jarrow	my constituency	has continued to welcome people
marchers ,		from throughout the UK ,
and not-for-profit groups , of	my constituency	, doing immensely valuable work .
which there are many in		They all too often
as soon as possible . Indeed , for	my constituents	, reform is already coming too
some of		late . \ n
bus travel in Wales . I have met	my constituency	who say that it has transformed
pensioners in		their lives . As
and Sir Malcolm Thornton . All	my constituency	and all left this House on 20
have represented part of		April or 1
Ports is the operator at the port	my constituency	. The companies there firmly
of Immingham in		believe that they have paid
Conservative-controlled Bradford	my constituency	from the free swimming initiative
city council excluded the		for young people and pensioners
wonderful Ilkley lido in		
for my hon . Friend's reply , and	my constituents	who have come across the benefit
many of		integrity project will be
Tero was not properly treated	my constituent	deserves . \ n "
and offer the apology that		

Table 21: A random sample of KWIC's (*continued*)

Pre	Keyword	Post
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 ,	my constituency	but in many northern towns and cities , I see
not only in	my constituents	. While I appreciate the cross-party consensus that exists on
on an issue that has been of great concern to		
In	my constituency	of West Lancashire , the national lottery has supported 266
to meet the skills gap in engineering and construction in	my constituency	. \ n " , " 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	my constituency	on the pensioners tax credit was extremely successful . The
consultation in 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	my constituency	, has so far concentrated CCTV bids-I am sure with
Westminster , which covers half also significant gaps in the Bill .	my constituency	concerns a community hydro project in Saddleworth that might not
One example from		
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	my constituency	, with which I am dealing , involves elderly victims
. Another case in		
. \ n " , " The credit union in	my constituency	is fragile , because it serves an area in which
certainly applies to me because	my constituents	, who desperately need care , has the mother and
the acute trust that covers reveal a trend , and I see it	my constituency	. It is a demonstrable fact that the polarisation between
happening in	My constituent	, John Warren , has specifically asked me to raise
\ n " , " Bridges Project in Musselburgh in	my constituency	does a brilliant job in supporting young people . A
Spewart , 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	. \ n "
	My constituents	in Hull are baffled by the Government's approach . At
issue and go after these criminals who are preying on	my constituents	?

Table 21: A random sample of KWIC's (*continued*)

Pre	Keyword	Post
even begin for another 12 months	my constituency	should not have to spend another
. Young people in		year on the dole
with the nutrition they need	my constituency	, several schools run summer
outside term time . In		programmes funded through the
		pupil
takes umbrage at being forced to	my constituents	, sadly , know to their cost . \ n
do repairs-as some of		
" , " I recently visited a care	my constituency	that is provided by a small
home in		charity and is rated
House and members of the armed	my constituent	, 19-year-old Private James
forces , such as		Kenny of C company , 3rd
as out to Kent . There are seven	my constituency	: Hither Green , Blackheath , Lee
stations in		, Grove Park
Can my right hon . Friend give	my constituent	, Mr . Peter Dyson , who has
any assurance to		written to
Commons Library to conduct an	my constituency	. I discovered that 4,300 women
analysis of the impact in		and 3,800 men would
100 days of the new Parliament ?	my constituency	are struggling significantly and
Many businesses in		would undoubtedly welcome a
		period of
in 1992 , as the Member for	my constituency	was formed for the 1997 election .
Woolwich , before		John Austin is
were building up and seemed to	my constituents	had suffered a very high level of
take action only once		nuisance and there
that further education	my constituency	, will not receive a real-terms
institutions , such as Blackburn		funding cut as a
College in		
n " , " On a more serious note ,	my constituency	is home to manufacturers varying
		from Corus to Cadbury ,
costs and cuts to working tax	my constituency	will be worse off . I will not vote
credits , families in		in
be warm . It paid for basics like	my constituency	. I will not revisit the pain of
that in		tuition fees
is a national issue . The 900 steel	my constituency	whose jobs are on the line expect
workers in		him to guarantee
to begin by speaking about the	my constituents	. Getting an appointment to see
NHS as experienced by		a GP can be
I was struck by what one of	my constituents	said last weekend , which was
		that the attacks that
n " , " On 18 February ,	my constituency	hosted the first North Wales
Llandudno in		criminal justice board conference
		.
my hon . Friend foresee for the	my constituency	if they are to suffer possible cuts
young people in		alongside that idiosyncratic
busways and widen the M1 . Is	my constituency	will have the new Translink
he aware that		guided busway by 2008 due
" Last week , I hosted a jobs fair	my constituency	, as have many hon . Members
in		on both sides
in the south-east will be dealt	My constituents	want to know where we are going
with in Parliament ?		and what the
him to visit the brand-new	my constituency	, which is due to open in January
children's centre in Elland in		, and

Table 21: A random sample of KWIC's (*continued*)

Pre	Keyword	Post
realities for people affected by this situation . One of the past few days . When the problems started in those branches , in Catford and Blackheath , are in	my constituents my constituency my constituency My constituent	is stuck out in Saudi Arabia . His work has on Monday night , we saw copycat criminality , mindless and two others , in Lewisham and Greenwich , are , Richard Belmar , has now spent nearly three years . I fully accept many of my hon . Friend's
Postwatch because I am unhappy about the consultation process in area of Keighley last Friday and talking to many of of the major issues raised with me by carers in that the voucher company Farepak , which is based in scientific reports recommend restricted phone use by younger children . . Mullin) . This is a big issue in	my constituency my constituents my constituency my constituency My constituents my constituency	and taking on board many of their anxieties . On . We must take such issues on board . \n , collapsed this week , robbing thousands of people on do not believe that such recommendations tally with the telecommunications , where inappropriate development on garden sites is taking place
scrutiny process , but it is impossible for me , " , " At the time , I was consulting	my constituents my constituents	or councillors of any party not involved in that enterprise about their attitudes to crime and antisocial behaviour , and is served by two hospitals :
you prove it ? " \n " , "	My constituency	Dewsbury and District hospital and firefighters that those latest cuts will not jeopardise or has lost funding and can no longer employ its part-time
% reduction . What reassurances can the Minister give to . \n " , " Horwich visiting service in	my constituents my constituency	
I have spoken to many businesses in prevent businesses from going into administration , as many in I do not know whether my experience in ? \n " , " Many SMEs operate in	my constituency my constituency my constituency my constituency	. Will the hon . Gentleman concede that the Government's are likely to do . Finally , the local authority has been exactly the same as that of my right , and I want to ensure that the skills base
that population live in Salford , the local authority for	my constituency	. \n " , " In last year's debate
It is an issue that has been simmering away in of the parenting lessons that go on in schools in a distraught couple who run a hedgehog rescue centre in people to think that that was the total sum of	my constituency my constituency my constituency my constituency	and recently the rumours have turned to reality as the to great effect . The hon . Gentleman ignores those . They are currently nursing back to health a hedgehog . It is an extremely nice place to spend Christmas

Table 21: A random sample of KWIC's (*continued*)

Pre	Keyword	Post
transparency about the impact . \ n " , "	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	. \ n " , " 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 .	my constituency	are concerned that Government
Head teachers in	my constituency	have still not come forward with
the work of local authorities in	my constituency	, there are no high profile arts venues that hit
my area . In	my constituency	might not have succeeded under the proposed 75 per cent
many of the early asbestosis claims from Hebden Bridge in	My constituency	is pronounced \ " Erreywash \ " , not \
job first . \ " \ n " , "	my constituents	, who have small sums of money available to invest
that is not regulated properly ,	my constituency	have seen many pictures before .
with the result that	my constituency	I want work to
a picture of the winning design ,	my constituency	over the last few weeks , and they tell me
but people in	my constituents	. It is 20 years to the month that post-war
hour . I have written to all the headteachers in	my constituency	, talk to me about how excited they still are
this debate falls on an anniversary well worth	my constituency	, which has got a new science lab and sports
remembering for	my constituents	? I would be happy to do that . \
people of the east end , including	my constituency	over the past 10 years or so . For the
the people of	My constituents-hundreds	of whom have written to me-overwhelmingly feel that he
I recently visited Bishop	my constituents	has
Barrington school in	my constituents	knew whether to laugh or cry . \
the extent of the disruption and	my constituency	n "
the problems caused for	my constituents	. The new local improvement finance trust-LIFT-centre will
increase in the number of new	My constituents	include GP
homes being built in	my constituency	are only too well aware of the exploitative practices of
junior doctors who are the	my constituents	at the university of Durham , which concentrates on enabling
problem , but him ?	my constituents	will find most amusing .
, \ n " , " I do not think	my constituents	but for the public as a whole .
about to be built in Walkden in	my constituents	The revenue
the centre of	my constituents	, which currently number at least six , tell me
is higher , and the dole queue is lengthening .	my constituents	
" I am fortunate in having a	my constituents	
research centre in	my constituents	
is talking about the wrong	my constituents	
hospital , which many of	my constituents	
of the Land Registry would be	my constituents	
bad not just for	my constituents	
The food banks in	my constituents	

Table 21: A random sample of KWIC's (*continued*)

Pre	Keyword	Post
of those issues . \ n " , " 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	my constituents	still face the prospect of seriously downgraded services at their
campaign . But for now , from and bugbear for my	my constituents	and their families , I very much look forward to
constituents . On behalf of " , " helped motorists and the	my constituency-or	they could have looked at jobs for young people .
hard-pressed hauliers in		
Staff at Trinity , Bluecoat and Fernwood schools in	my constituency	are desperate for extra investment in their buildings .
The point about geography is critical in Cumbria , where	my constituency	Will is . Under the proposals , we will end up
will affect disabled youngsters .	my constituency	, which gives counselling to all youngsters , still does
The What ? centre in	my constituency	. Walsall faces the closure of its HMRC office ,
closure of the offices is having a direct impact on		: for many years , they have felt marginalised and
. \ n " , " Frustration is evident among	my constituents	
, larger numbers of people are choosing to live in	my constituency	but work in London . If we are to take
ethnic minority children , of	my constituency	. \ n " , " We have dealt a
whom there are many in		
single parents in the country-I	my constituents	think that the measure is unfair .
will return to that point-and		How people in
should not come back from our	my constituents	, and those of my neighbours , have lost their
holidays to find that		. \ n " , " We also need better
their area ; I fully intend to do so in	my constituency	
too much movement . I want	my constituency	not just to survive , but to prosper . It
Airedale general hospital in		and those of many other hon .
" , " During the summer and	my constituents	Members were affected
autumn months ,	my constituents	experience . \ n " , " In Newham
put a human face on many of the		,
difficulties that		. It has just received nearly £
Parent Action Network , which	my constituency	400,000 in lottery
has its national headquarters in		told me that he estimated that
sector . On Friday , an	my constituency	the Government cuts would
independent community		
pharmacist in		
it becomes an empty gesture . A	my constituency	is setting up a community
community group in		development trust , and it
since June and doubled since	my constituency	have been particularly badly hit ,
2006 . Young people in		with a 288 %
police get back to strength to	my constituency	of Mitcham and Morden ?
defend the people in		

Table 21: A random sample of KWIC's (*continued*)

Pre	Keyword	Post
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	my constituency	in particular . Will the Minister assure the House that
massive economic opportunity for Wales and		
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	. \ n " , " These are ideologically driven
deal more about the birdlife in both estuaries that surround	my constituency	. \ n " , " 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 . \ n " , " 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 .
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

Table 21: A random sample of KWIC's (*continued*)

Pre	Keyword	Post
first home . There are so many	my constituency	who see homes priced out of their
young people in		reach and for
There are also problems for	my constituent	on Colleymoor Leys lane who
low-income families , such as		says : \ n "
term . I know from the	my constituency	and in the surrounding west
experience of businesses in		midlands area that New Street
that he needs those , but he	my constituents	watching yesterday that a 1p cut
failed to tell		in duty will not
average , which show that over a	my constituency-of	people who resort to food banks
fifth-22 % in		for an emergency food

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