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 where classified the same as if they had not been suspended. The dataset includes 408 different Labour MPs, 167 female MPs, 119 elected from All Women Shortlists and 48 elected from open shortlists, along with 241 male MPs.

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)

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

- Words longer than six letters (Sixltr)

We also included mean words-per-sentence (WPS), total speach word count (WC) and Flesch–Kincaid grade level (FK) (Kincaid, 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 occurences of selected LIWC terms, words-per-sentence, total word count and Flesch–Kincaid grade level, over the course of an MP's career. There do not appear to be any notable changes in speaking style over the course of female Labour MPs' careers.

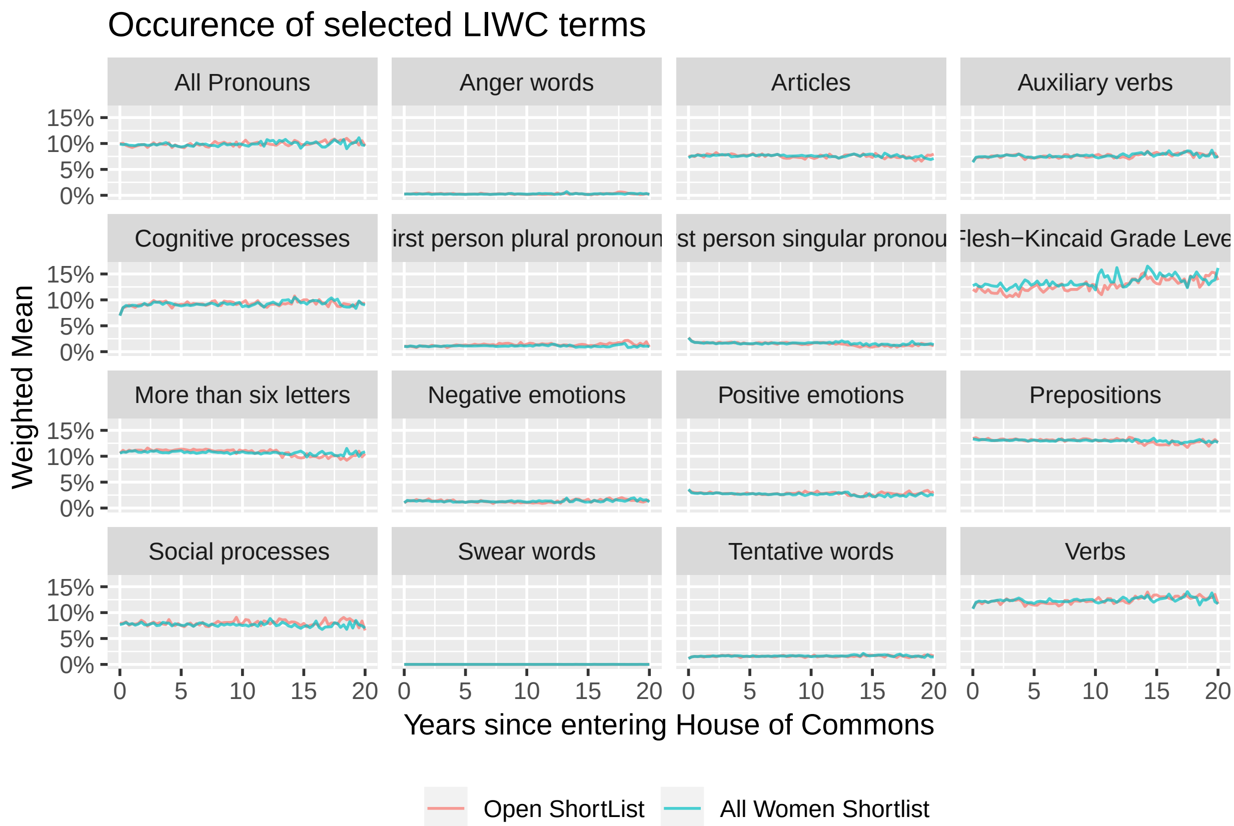

Figure 1: Occurence of selected LIWC terms

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

	All Women Shortlists		Open Shorlists		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

	Women		Men		Effect Size	
Word Type	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Nouns	22.17	9.56	21.67	10.92	-0.05	negligible
Plural Nouns	5.86	3.71	5.04	3.79	-0.22	small
Singular Nouns	15.61	9.81	16.01	11.16	0.04	negligible
Adjectives	9.58	4.77	9.28	5.29	-0.06	negligible
Adverbs	4.91	4.25	5.06	4.91	0.04	negligible
Verbs	20.97	9.52	20.81	10.28	-0.02	negligible

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

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

Part-of-speech (POS) tagging was done using `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 $d >= |0.2|$ 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.

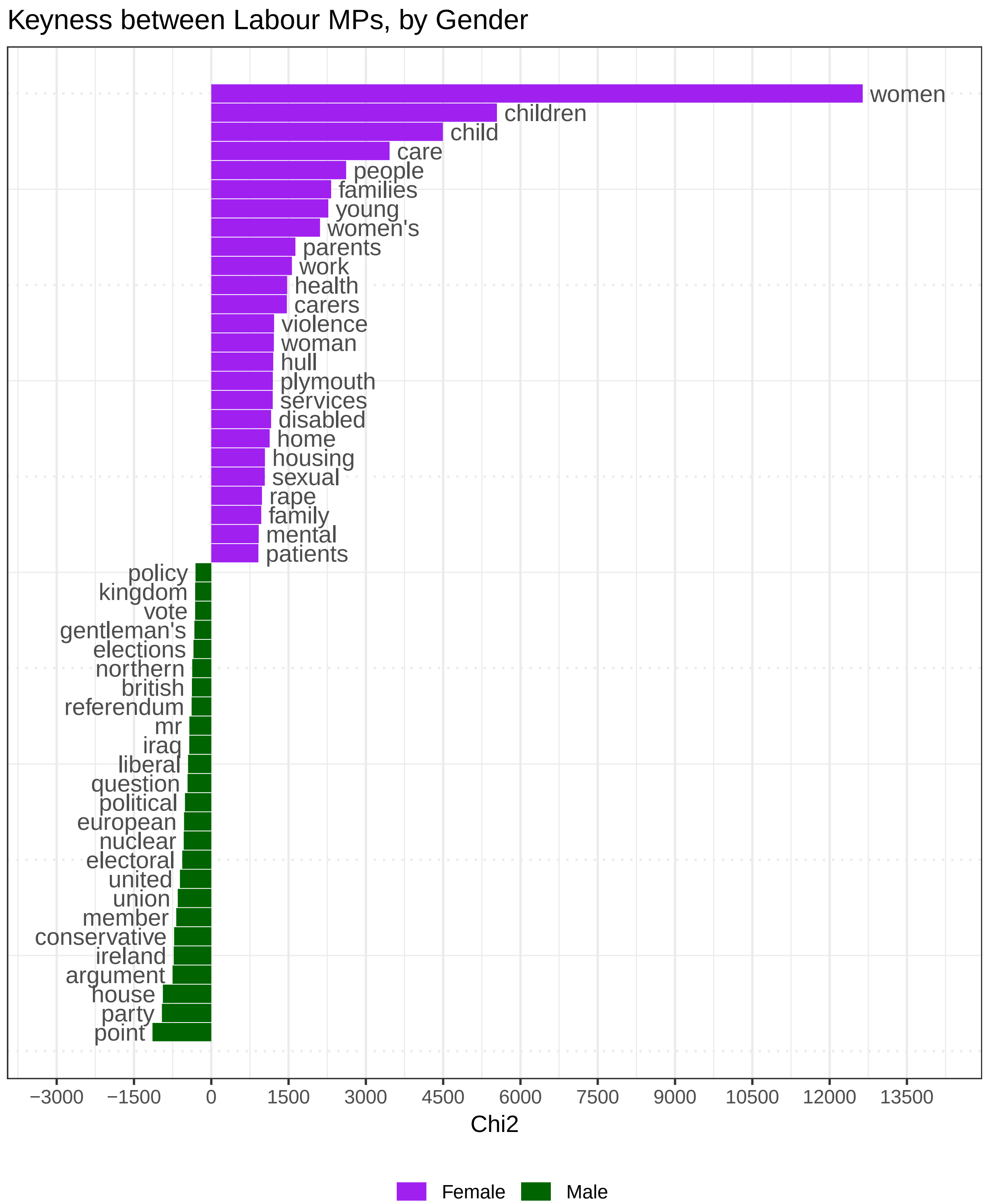

Figure 2: Keyness between Labour MPs, by Gender

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.

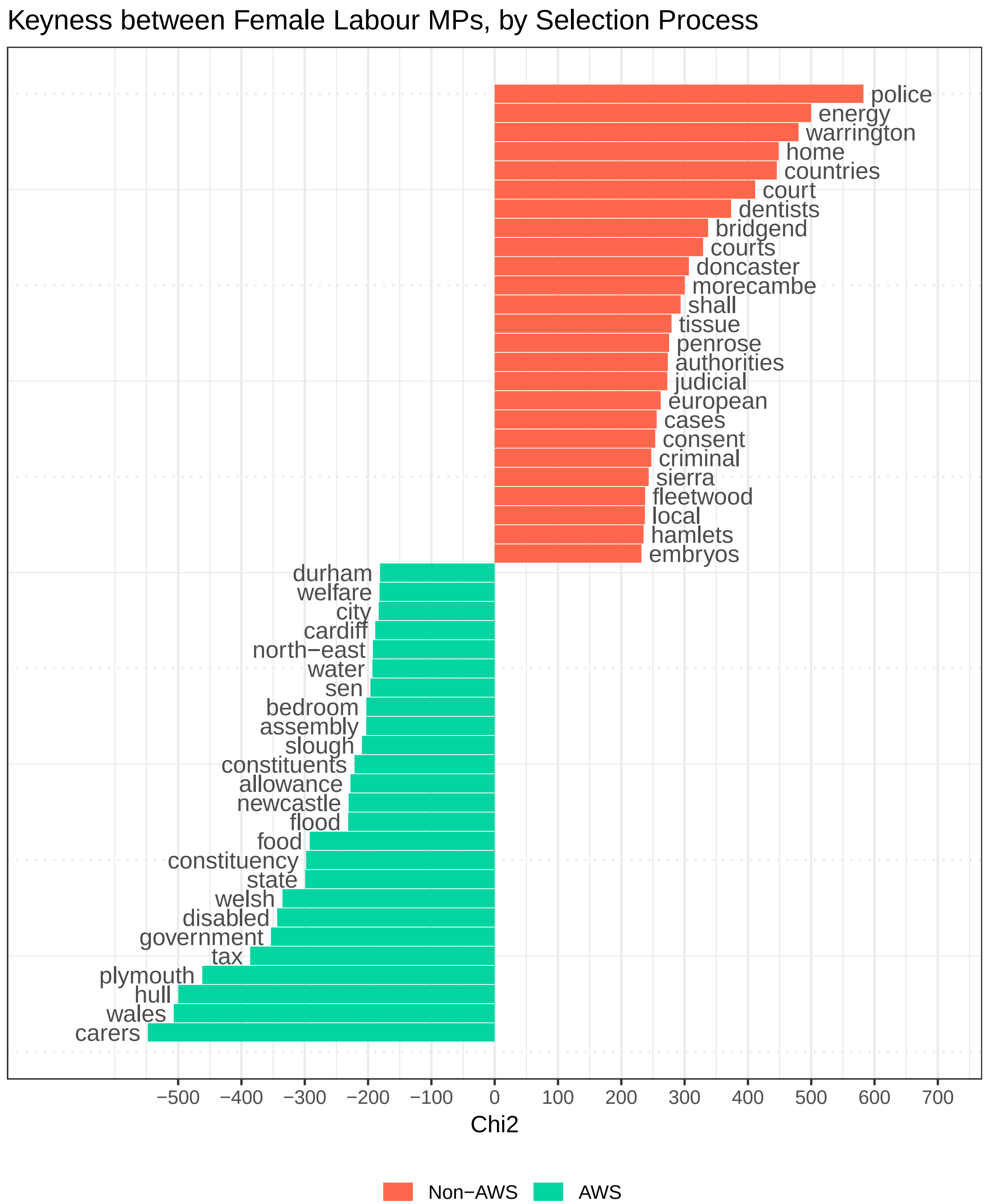

Figure 3: Keyness between Female Labour MPs, by Selection Process

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 hosue decorum by Conservative MPs.

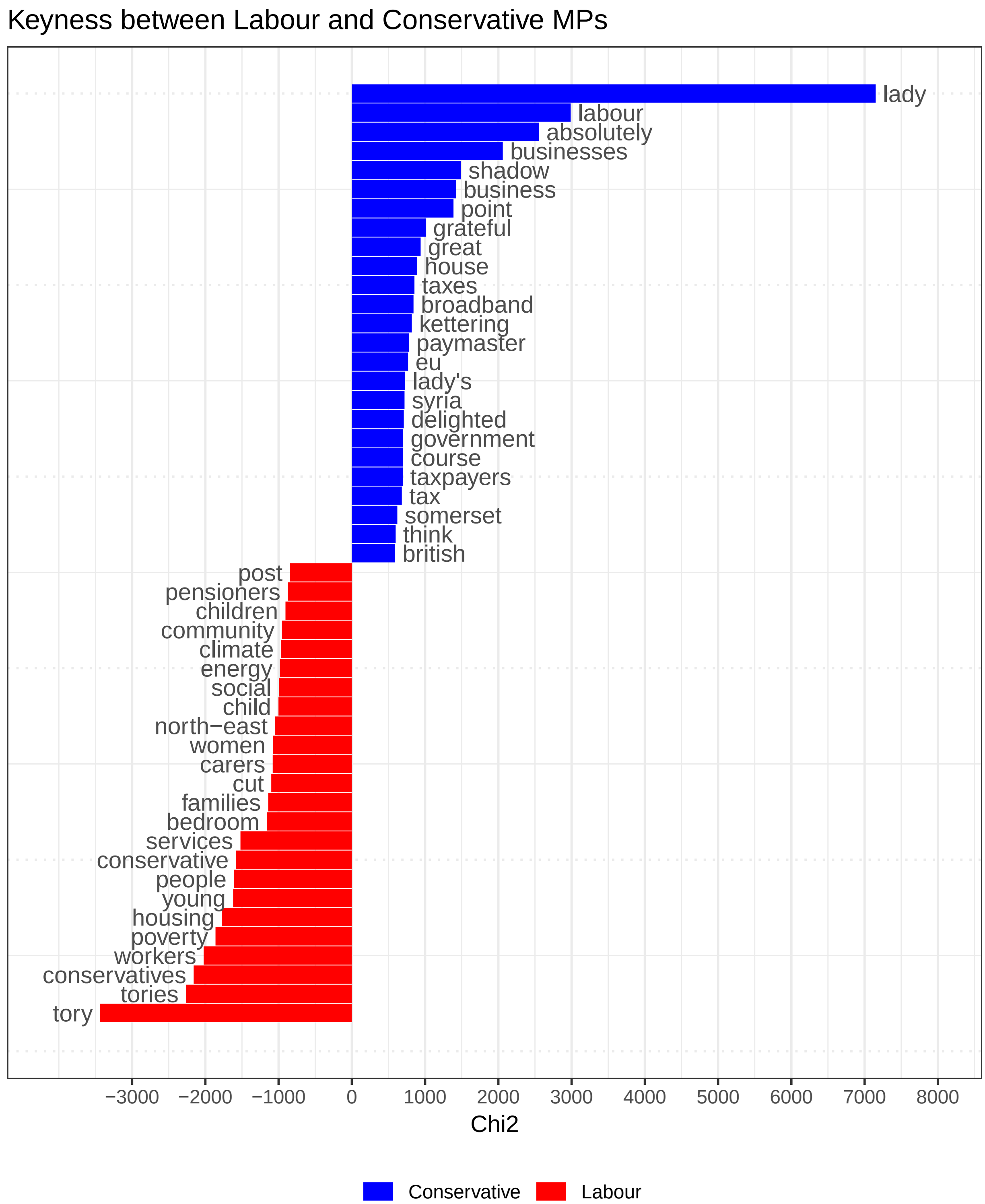

Figure 4: Keyness between Labour and Conservative MPs

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.

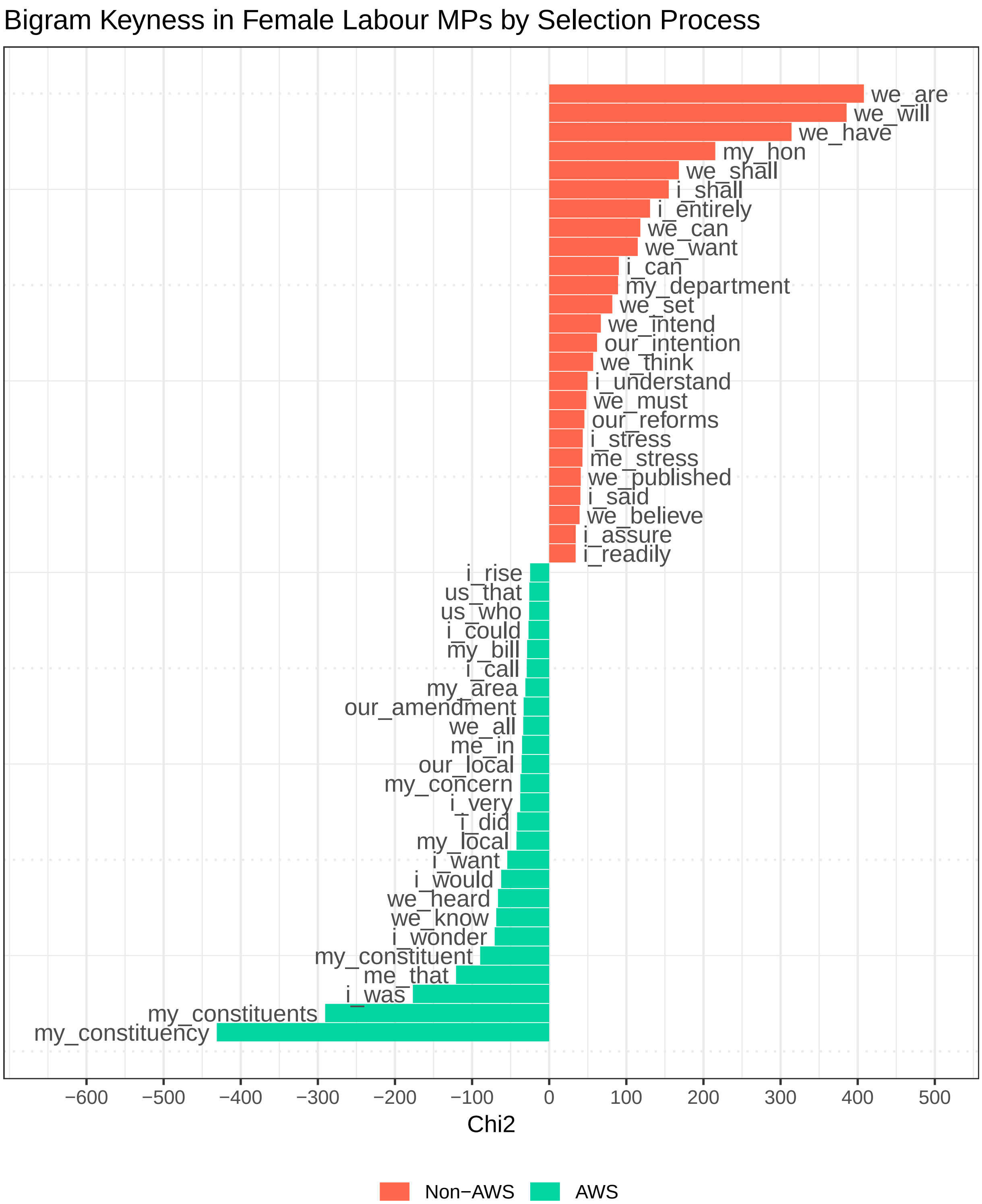

Figure 5: Bigram Keyness in Female Labour MPs by Selection Process

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 unsurpervised 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 speechs 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 speechs 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 20, and the appendix), or contain only a small number of speeches.

2.6.1 Shortlists vs Non-Shortlists - K30

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 30 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 accurate hand-coding of topics more straightforward. The topic model has 81,651 documents and uses a dictionary of 119,586 words.

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.

- check citations of roberts 2016 to see how other people use it/select K

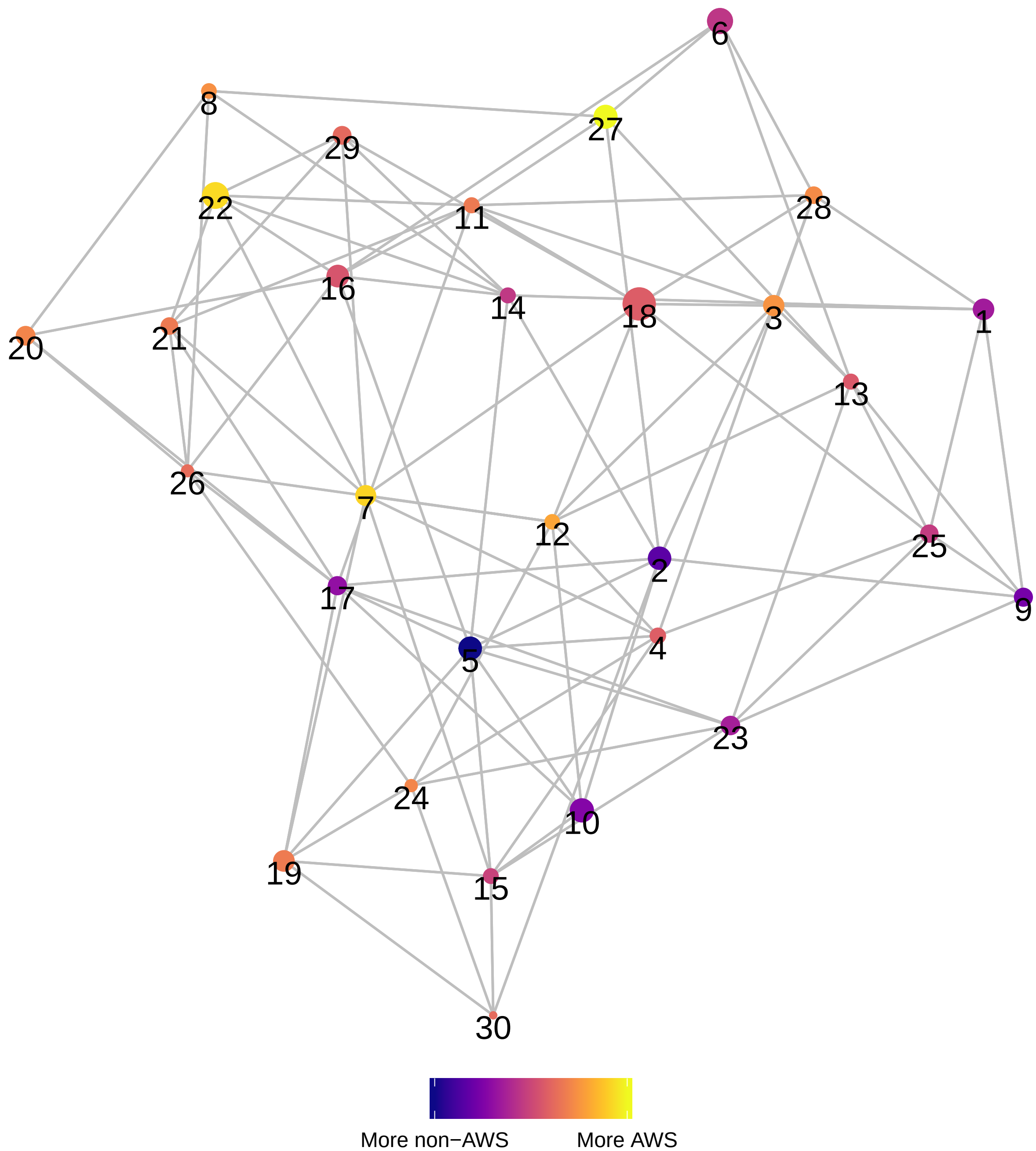

Figure 6: Fruchterman-Reingold plot of K30 Network

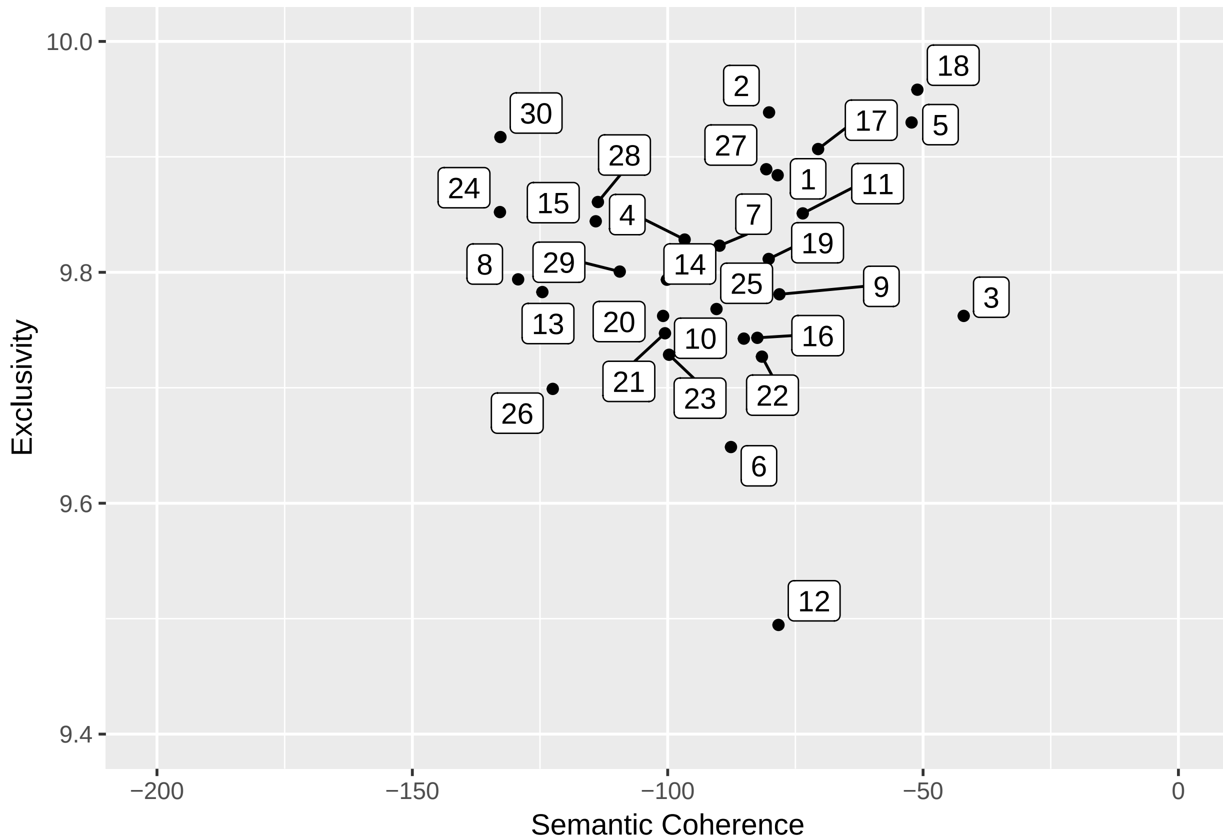

Figure 7: Coherence of K30 Topic Models

[INSERT ANALYSIS AND DISCUSSION OF GRAPH]

The `stm` package includes the `estimateEffect` function to create a regression model 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.

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 aforemention and "people", p values of < 0.001.

Table 9: Topic Estimates

	Estimate	Standard Error	t value	Pr(>|t|)	
Topic 1 – Bills					
Intercept	0.0458851	0.0006705	68.4341958	< 0.001	***
Shortlist	-0.0075297	0.0008280	-9.0933469	< 0.001	***
Topic 2 – Consultations					
Intercept	0.0649549	0.0005490	118.3116946	< 0.001	***
Shortlist	-0.0140282	0.0006328	-22.1685938	< 0.001	***
Topic 3 – Members					
Intercept	0.0399386	0.0005207	76.7077203	< 0.001	***
Shortlist	0.0062858	0.0006521	9.6397704	< 0.001	***
Topic 4 – Gender					
Intercept	0.0221346	0.0005903	37.4987768	< 0.001	***

Table 9: Topic Estimates *(continued)*

	Estimate	Standard Error	t value	Pr(>|t|)	
Shortlist	0.0006003	0.0006940	0.8649482	0.39	
Topic 5 – Civic society					
Intercept	0.0713503	0.0005554	128.4766813	< 0.001	***
Shortlist	-0.0196372	0.0006453	-30.4328455	< 0.001	***
Topic 6 – International					
Intercept	0.0459985	0.0008978	51.2346194	< 0.001	***
Shortlist	-0.0041550	0.0011146	-3.7279005	< 0.001	***
Topic 7 – Disability					
Intercept	0.0268142	0.0005613	47.7704056	< 0.001	***
Shortlist	0.0121386	0.0007564	16.0482872	< 0.001	***
Topic 8 – Rural Issues					
Intercept	0.0142017	0.0004652	30.5290460	< 0.001	***
Shortlist	0.0060359	0.0005993	10.0708450	< 0.001	***
Topic 9 – Immigration					
Intercept	0.0364690	0.0006409	56.9058562	< 0.001	***
Shortlist	-0.0116339	0.0007642	-15.2243758	< 0.001	***
Topic 10 – Health Care					
Intercept	0.0435531	0.0007359	59.1810374	< 0.001	***
Shortlist	-0.0103351	0.0009241	-11.1842320	< 0.001	***
Topic 11 – Parties					
Intercept	0.0318562	0.0004360	73.0702029	< 0.001	***
Shortlist	0.0036434	0.0005779	6.3042791	< 0.001	***
Topic 12 – Constituencies					
Intercept	0.0224526	0.0005080	44.2007923	< 0.001	***
Shortlist	0.0080764	0.0006398	12.6232862	< 0.001	***
Topic 13 – Security					
Intercept	0.0229239	0.0004963	46.1895581	< 0.001	***
Shortlist	-0.0000212	0.0006049	-0.0351024	0.97	
Topic 14 – Investment					
Intercept	0.0262756	0.0005276	49.7994193	< 0.001	***
Shortlist	-0.0039488	0.0006423	-6.1483502	< 0.001	***
Topic 15 – Youth					
Intercept	0.0229403	0.0005679	40.3940609	< 0.001	***
Shortlist	-0.0027495	0.0006871	-4.0018251	< 0.001	***
Topic 16 – Energy					
Intercept	0.0358292	0.0007101	50.4530884	< 0.001	***
Shortlist	-0.0005328	0.0009114	-0.5846086	0.56	
Topic 17 – Local authorities					
Intercept	0.0398910	0.0005093	78.3244019	< 0.001	***
Shortlist	-0.0089605	0.0006075	-14.7501767	< 0.001	***
Topic 18 – People					
Intercept	0.0846597	0.0005574	151.8702262	< 0.001	***
Shortlist	0.0003645	0.0007085	0.5145246	0.61	
Topic 19 – Education					
Intercept	0.0282651	0.0007023	40.2441826	< 0.001	***
Shortlist	0.0038527	0.0008216	4.6894827	< 0.001	***

Table 9: Topic Estimates *(continued)*

	Estimate	Standard Error	t value	Pr(>|t|)	
Topic 20 – Transport					
Intercept	0.0228207	0.0006019	37.9173245	< 0.001	***
Shortlist	0.0049460	0.0007977	6.2002809	< 0.001	***
Topic 21 – Housing					
Intercept	0.0202285	0.0005997	33.7316675	< 0.001	***
Shortlist	0.0037347	0.0007093	5.2655652	< 0.001	***
Topic 22 – Tax					
Intercept	0.0440582	0.0008233	53.5134233	< 0.001	***
Shortlist	0.0126836	0.0010388	12.2098712	< 0.001	***
Topic 23 – Police					
Intercept	0.0300319	0.0006151	48.8253431	< 0.001	***
Shortlist	-0.0070584	0.0008011	-8.8105114	< 0.001	***
Topic 24 – Media					
Intercept	0.0112179	0.0004447	25.2235247	< 0.001	***
Shortlist	0.0049899	0.0005035	9.9094420	< 0.001	***
Topic 25 – Families					
Intercept	0.0257936	0.0006255	41.2381646	< 0.001	***
Shortlist	-0.0035687	0.0007992	-4.4652995	< 0.001	***
Topic 26 – Environment					
Intercept	0.0145323	0.0004357	33.3504477	< 0.001	***
Shortlist	0.0022731	0.0005658	4.0175379	< 0.001	***
Topic 27 – Ministers					
Intercept	0.0419254	0.0005314	78.9016318	< 0.001	***
Shortlist	0.0151703	0.0006856	22.1264693	< 0.001	***
Topic 28 – Regions					
Intercept	0.0228733	0.0005245	43.6080641	< 0.001	***
Shortlist	0.0055461	0.0006772	8.1893341	< 0.001	***
Topic 29 – Pensions					
Intercept	0.0265485	0.0005807	45.7203048	< 0.001	***
Shortlist	0.0017382	0.0007334	2.3702268	0.018	*
Topic 30 – Technology					
Intercept	0.0135812	0.0003344	40.6094477	< 0.001	***
Shortlist	0.0020698	0.0004246	4.8751764	< 0.001	***

Table 10: 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

Table 10: Distribution of Topics Among Female Labour MPs – K30
(continued)

Topic	One or more speeches	Five or more speeches
Local authorities	151	100
People	165	146
Education	153	115
Consultations	156	107
Transport	157	102
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 11: 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%	8,178	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%	1,839	6.6%	7,616	4.5%
International	3,138	5.83%	1,891	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%

Table 11: 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
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%	30,542	18.04%
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%	6,217	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%

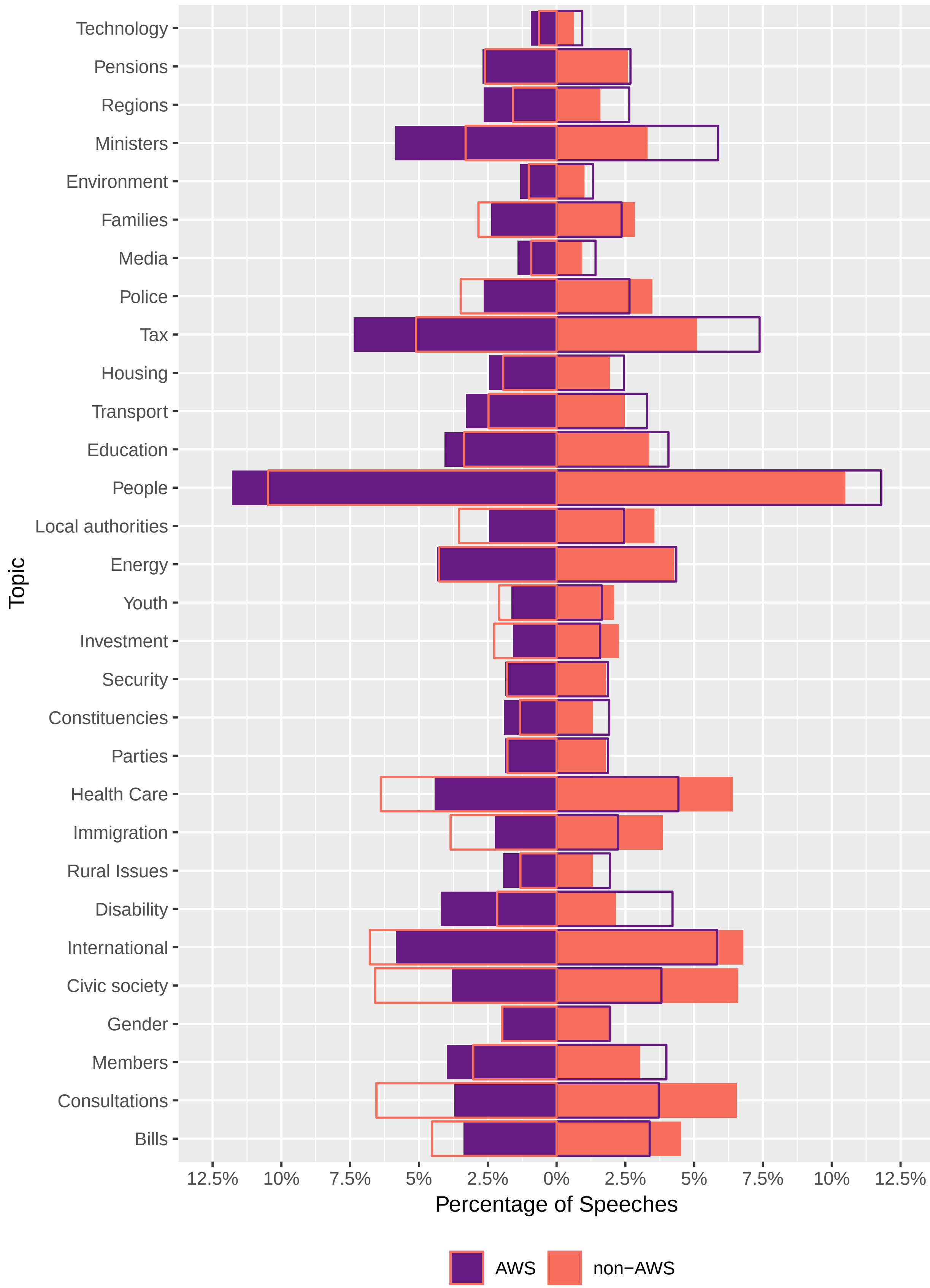

Figure 8: K30 Pyramid Chart

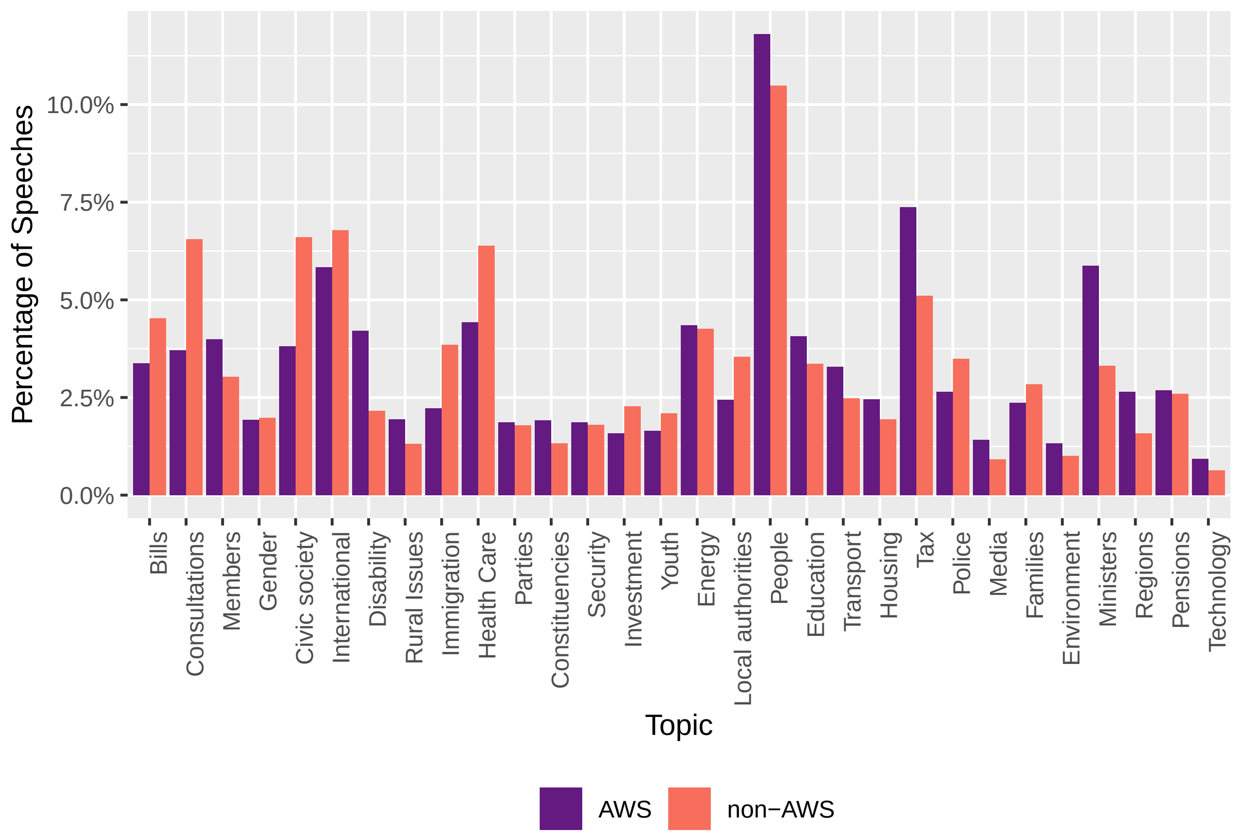

Figure 9: K30 Bar Chart

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 10 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 10: K30 Topic Proportions

2.6.1.1 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 12: 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 12: 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 12: 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, gcses, 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 12: 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

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, than the Labour MP for West Dunbartonshire (elected on an AWS in 2010), when asked if she would give way to Conservative MP Stephen Mosley, responded:

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

On 2nd June 2010, during debate on Israel-Palestine, Valerie Vaz, MP for Walsall South:

> 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

4.1.1 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, cdfi, 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, @leamingtonsbc
##       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
```

4.1.2 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)     0.0458761  0.0006707  68.405 <0.0000000000000002 ***
## short_listTRUE -0.0075205  0.0008312  -9.047 <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)     0.0649475  0.0005421  119.80 <0.0000000000000002 ***
## short_listTRUE -0.0140269  0.0006211  -22.58 <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)    0.0399413  0.0005153  77.506 <0.0000000000000002 ***
## short_listTRUE 0.0062813  0.0006537   9.609 <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)    0.0221319  0.0005920  37.385 <0.0000000000000002 ***
## short_listTRUE 0.0006031  0.0006972   0.865               0.387
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 5:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0713472  0.0005577   127.9 <0.0000000000000002 ***
## short_listTRUE -0.0196321  0.0006478   -30.3 <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)     0.0459947  0.0008968  51.287 < 0.0000000000000002 ***
## short_listTRUE -0.0041526  0.0011042  -3.761              0.00017 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0268154  0.0005613   47.77 <0.0000000000000002 ***
## short_listTRUE 0.0121378  0.0007539   16.10 <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)    0.0141907  0.0004701  30.185 <0.0000000000000002 ***
## short_listTRUE 0.0060476  0.0006083   9.942 <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)     0.0364767  0.0006401   56.99 <0.0000000000000002 ***
## short_listTRUE -0.0116365  0.0007564  -15.38 <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)     0.0435555  0.0007402   58.84 <0.0000000000000002 ***
## short_listTRUE -0.0103426  0.0009342  -11.07 <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)    0.0318549  0.0004346  73.297 < 0.0000000000000002 ***
## short_listTRUE 0.0036470  0.0005794   6.294       0.000000000311 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 12:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0224595  0.0005090   44.13 <0.0000000000000002 ***
## short_listTRUE 0.0080633  0.0006411   12.58 <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)     0.02292517  0.00050230  45.641 <0.0000000000000002 ***
## short_listTRUE -0.00001892  0.00060441  -0.031               0.975
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0262843  0.0005303  49.564 < 0.0000000000000002 ***
## short_listTRUE -0.0039607  0.0006465  -6.126       0.000000000903 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0229333  0.0005590  41.027 < 0.0000000000000002 ***
## short_listTRUE -0.0027330  0.0006837  -3.998             0.000064 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 16:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
```

```
## (Intercept)     0.0358349  0.0007060  50.758 <0.0000000000000002 ***
## short_listTRUE -0.0005412  0.0009103  -0.595               0.552
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 17:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0398841  0.0005100   78.21 <0.0000000000000002 ***
## short_listTRUE -0.0089603  0.0006056  -14.79 <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)    0.0846634  0.0005570 152.005 <0.0000000000000002 ***
## short_listTRUE 0.0003663  0.0006976   0.525               0.599
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 19:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0282646  0.0006992   40.42 < 0.0000000000000002 ***
## short_listTRUE 0.0038525  0.0008249    4.67           0.00000301 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0228157  0.0005977  38.175 < 0.0000000000000002 ***
## short_listTRUE 0.0049512  0.0007900   6.267       0.000000000369 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0202330  0.0006000  33.722 < 0.0000000000000002 ***
## short_listTRUE 0.0037307  0.0007047   5.294           0.00000012 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
##
## Topic 22:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0440676  0.0008103   54.38 <0.0000000000000002 ***
## short_listTRUE 0.0126783  0.0010314   12.29 <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)     0.0300357  0.0006050   49.65 <0.0000000000000002 ***
## short_listTRUE -0.0070633  0.0007866   -8.98 <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)    0.0112109  0.0004436  25.272 <0.0000000000000002 ***
## short_listTRUE 0.0049952  0.0005112   9.772 <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)     0.0257932  0.0006297  40.963 < 0.0000000000000002 ***
## short_listTRUE -0.0035581  0.0008047  -4.422           0.00000981 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0145425  0.0004387  33.151 < 0.0000000000000002 ***
## short_listTRUE 0.0022629  0.0005715   3.959            0.0000752 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
```

```
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0419228  0.0005269   79.56 <0.0000000000000002 ***
## short_listTRUE 0.0151734  0.0006798   22.32 <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)    0.0228755  0.0005272  43.391 < 0.0000000000000002 ***
## short_listTRUE 0.0055429  0.0006808   8.141 0.000000000000000396 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0265352  0.0005813  45.648 <0.0000000000000002 ***
## short_listTRUE 0.0017497  0.0007293   2.399              0.0164 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 30:
##
## Coefficients:
##                Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0135769  0.0003323  40.860 < 0.0000000000000002 ***
## short_listTRUE 0.0020744  0.0004250   4.882           0.00000105 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

4.2 K45

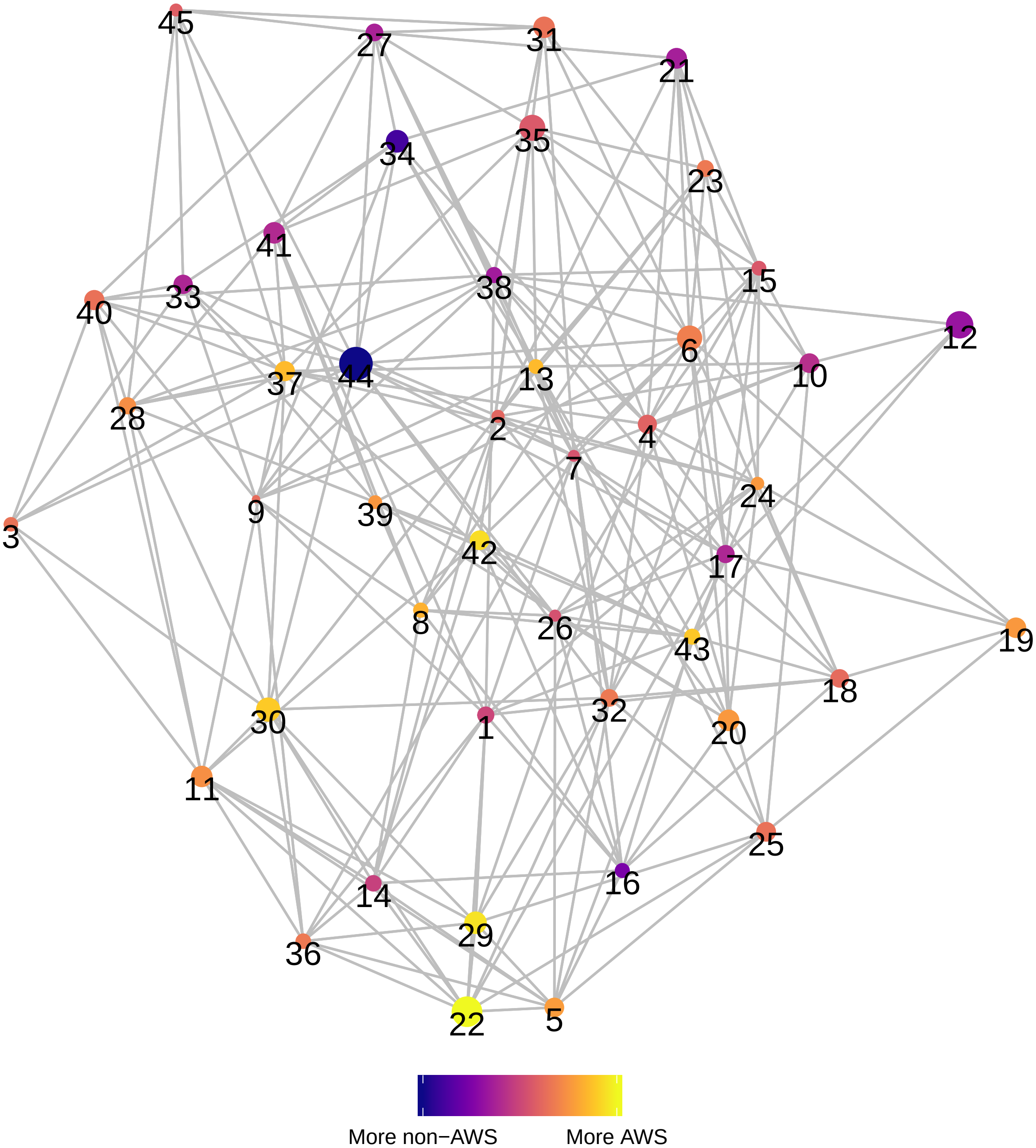

Figure 11: Fruchterman-Reingold plot of k45 Network

Table 13: Count and Distribution of Topics – k45

Estimate	Standard Error	t value	P	Topic	Type	Stars
0.0204928	0.0004320	47.4327090	0.0000000	1	Intercept	***
-0.0027710	0.0005633	-4.9194371	0.0000009	1	Shortlist	***
0.0111577	0.0003782	29.5023113	0.0000000	2	Intercept	***

Table 13: Count and Distribution of Topics – k45 *(continued)*

Estimate	Standard Error	t value	P	Topic	Type	Stars
0.0000039	0.0004479	0.0087239	0.9930395	2	Shortlist	
0.0181543	0.0003824	47.4734798	0.0000000	3	Intercept	***
0.0010563	0.0004720	2.2377364	0.0252409	3	Shortlist	*
0.0188180	0.0005099	36.9050984	0.0000000	4	Intercept	***
-0.0002303	0.0006432	-0.3580512	0.7203059	4	Shortlist	
0.0155084	0.0005405	28.6945309	0.0000000	5	Intercept	***
0.0041806	0.0006806	6.1423127	0.0000000	5	Shortlist	***
0.0369157	0.0003585	102.9811114	0.0000000	6	Intercept	***
0.0019894	0.0004492	4.4285238	0.0000095	6	Shortlist	***
0.0193246	0.0002798	69.0575536	0.0000000	7	Intercept	***
-0.0015243	0.0003374	-4.5180225	0.0000063	7	Shortlist	***
0.0088792	0.0003903	22.7467238	0.0000000	8	Intercept	***
0.0056221	0.0005572	10.0906049	0.0000000	8	Shortlist	***
0.0098211	0.0003656	26.8648166	0.0000000	9	Intercept	***
0.0004861	0.0004442	1.0943484	0.2738054	9	Shortlist	
0.0216443	0.0005632	38.4300027	0.0000000	10	Intercept	***
-0.0047511	0.0006995	-6.7922405	0.0000000	10	Shortlist	***
0.0315863	0.0004310	73.2896773	0.0000000	11	Intercept	***
0.0032215	0.0005311	6.0652793	0.0000000	11	Shortlist	***
0.0346266	0.0007008	49.4070184	0.0000000	12	Intercept	***
-0.0072089	0.0009182	-7.8514264	0.0000000	12	Shortlist	***
0.0117032	0.0003673	31.8631940	0.0000000	13	Intercept	***
0.0062230	0.0005047	12.3299782	0.0000000	13	Shortlist	***
0.0170256	0.0004543	37.4765769	0.0000000	14	Intercept	***
-0.0032584	0.0006109	-5.3334812	0.0000001	14	Shortlist	***
0.0166940	0.0003696	45.1627721	0.0000000	15	Intercept	***
-0.0011862	0.0004444	-2.6690751	0.0076075	15	Shortlist	**
0.0254953	0.0004368	58.3736714	0.0000000	16	Intercept	***
-0.0092972	0.0005065	-18.3574975	0.0000000	16	Shortlist	***
0.0259231	0.0004075	63.6099536	0.0000000	17	Intercept	***
-0.0055070	0.0005052	-10.9014935	0.0000000	17	Shortlist	***
0.0177185	0.0004516	39.2385580	0.0000000	18	Intercept	***
0.0004163	0.0005468	0.7613745	0.4464356	18	Shortlist	
0.0165343	0.0005354	30.8795104	0.0000000	19	Intercept	***
0.0039413	0.0006519	6.0458808	0.0000000	19	Shortlist	***
0.0181393	0.0005731	31.6495713	0.0000000	20	Intercept	***
0.0038830	0.0006720	5.7784174	0.0000000	20	Shortlist	***
0.0240657	0.0006114	39.3627910	0.0000000	21	Intercept	***
-0.0062053	0.0007277	-8.5273497	0.0000000	21	Shortlist	***
0.0361985	0.0006472	55.9351483	0.0000000	22	Intercept	***
0.0099944	0.0008356	11.9607287	0.0000000	22	Shortlist	***
0.0131312	0.0005654	23.2234335	0.0000000	23	Intercept	***
0.0015149	0.0006406	2.3648336	0.0180405	23	Shortlist	*
0.0082576	0.0003685	22.4068370	0.0000000	24	Intercept	***
0.0039137	0.0004518	8.6625850	0.0000000	24	Shortlist	***

Table 13: Count and Distribution of Topics – k45 *(continued)*

Estimate	Standard Error	t value	P	Topic	Type	Stars
0.0201204	0.0004766	42.2206024	0.0000000	25	Intercept	***
0.0008851	0.0005742	1.5415942	0.1231761	25	Shortlist	
0.0117479	0.0003736	31.4440569	0.0000000	26	Intercept	***
-0.0017157	0.0004538	-3.7809573	0.0001563	26	Shortlist	***
0.0214032	0.0004932	43.3950083	0.0000000	27	Intercept	***
-0.0059839	0.0005960	-10.0406597	0.0000000	27	Shortlist	***
0.0143877	0.0004557	31.5734810	0.0000000	28	Intercept	***
0.0031512	0.0005609	5.6183346	0.0000000	28	Shortlist	***
0.0198890	0.0005751	34.5816087	0.0000000	29	Intercept	***
0.0087461	0.0007178	12.1839815	0.0000000	29	Shortlist	***
0.0396879	0.0003934	100.8717706	0.0000000	30	Intercept	***
0.0072072	0.0004838	14.8983361	0.0000000	30	Shortlist	***
0.0327856	0.0004221	77.6660635	0.0000000	31	Intercept	***
0.0010300	0.0005363	1.9206800	0.0547755	31	Shortlist	
0.0267151	0.0003247	82.2721540	0.0000000	32	Intercept	***
0.0015673	0.0004080	3.8413145	0.0001225	32	Shortlist	***
0.0272196	0.0005581	48.7715522	0.0000000	33	Intercept	***
-0.0056690	0.0006417	-8.8337837	0.0000000	33	Shortlist	***
0.0323237	0.0005779	55.9320447	0.0000000	34	Intercept	***
-0.0127323	0.0007143	-17.8247870	0.0000000	34	Shortlist	***
0.0283347	0.0007093	39.9501174	0.0000000	35	Intercept	***
-0.0010502	0.0008753	-1.1997480	0.2302407	35	Shortlist	
0.0157212	0.0003778	41.6127816	0.0000000	36	Intercept	***
0.0015075	0.0004913	3.0686501	0.0021510	36	Shortlist	**
0.0236927	0.0003763	62.9608756	0.0000000	37	Intercept	***
0.0061838	0.0004973	12.4354577	0.0000000	37	Shortlist	***
0.0280890	0.0003819	73.5593255	0.0000000	38	Intercept	***
-0.0065506	0.0005176	-12.6550914	0.0000000	38	Shortlist	***
0.0109069	0.0003866	28.2125758	0.0000000	39	Intercept	***
0.0038218	0.0004988	7.6620062	0.0000000	39	Shortlist	***
0.0285154	0.0004152	68.6813864	0.0000000	40	Intercept	***
0.0009442	0.0004726	1.9978572	0.0457355	40	Shortlist	*
0.0259848	0.0005455	47.6317460	0.0000000	41	Intercept	***
-0.0052636	0.0006530	-8.0611831	0.0000000	41	Shortlist	***
0.0168814	0.0004332	38.9692812	0.0000000	42	Intercept	***
0.0083508	0.0005835	14.3123880	0.0000000	42	Shortlist	***
0.0132730	0.0004026	32.9664895	0.0000000	43	Intercept	***
0.0070793	0.0005323	13.2987521	0.0000000	43	Shortlist	***
0.0676843	0.0004218	160.4470374	0.0000000	44	Intercept	***
-0.0154112	0.0005275	-29.2159743	0.0000000	44	Shortlist	***
0.0168126	0.0003068	54.8077059	0.0000000	45	Intercept	***
-0.0005823	0.0003826	-1.5217965	0.1280640	45	Shortlist	

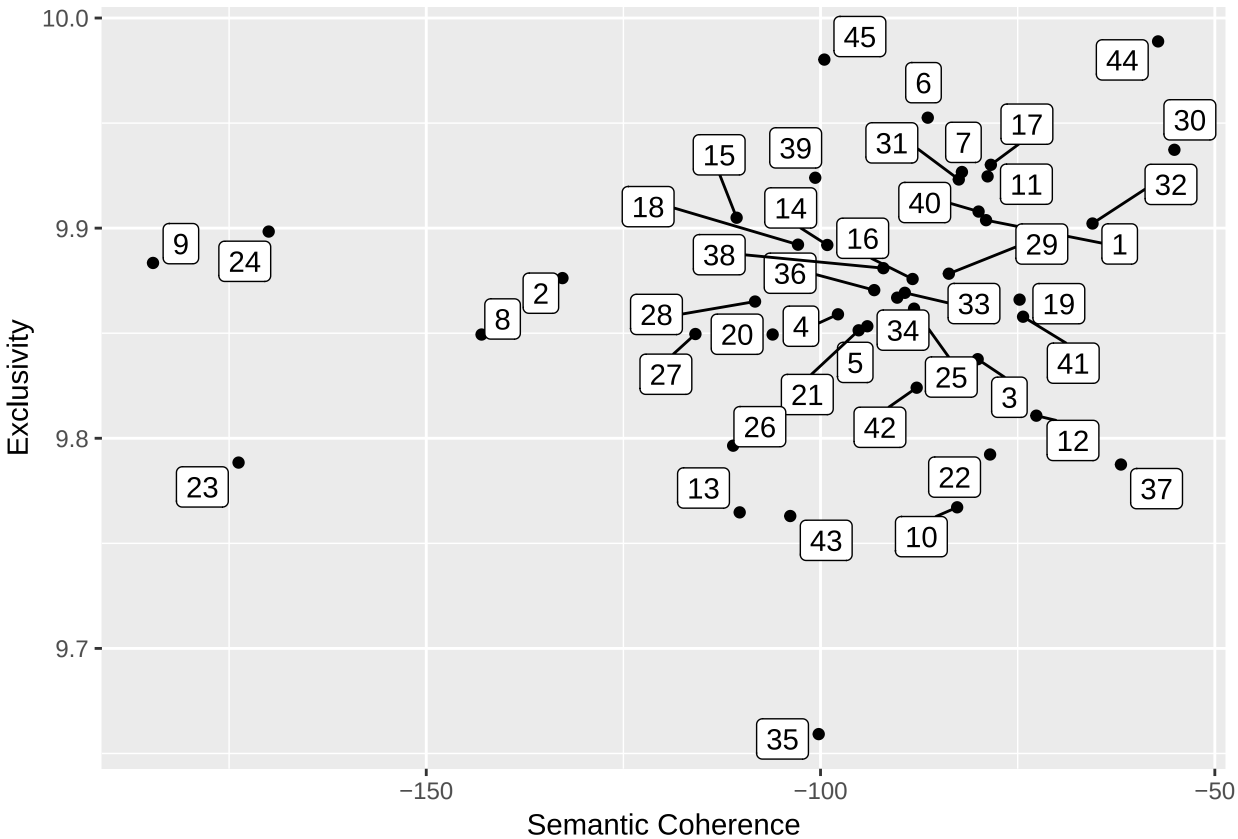

Figure 12: Coherence of k45 Topic Models

Table 14: 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%
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%

Table 14: 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 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%

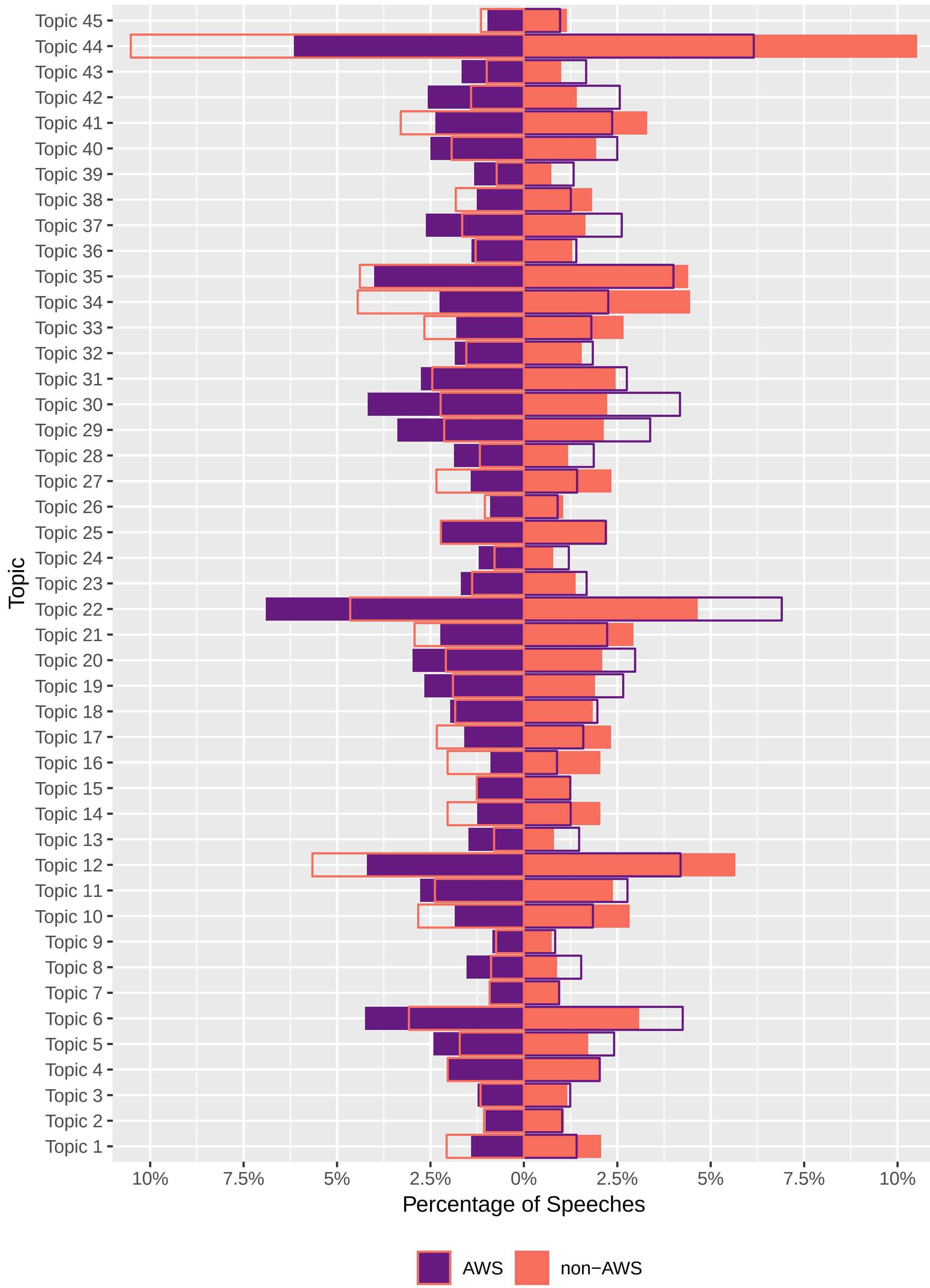

Figure 13: k45 Pyramid Chart

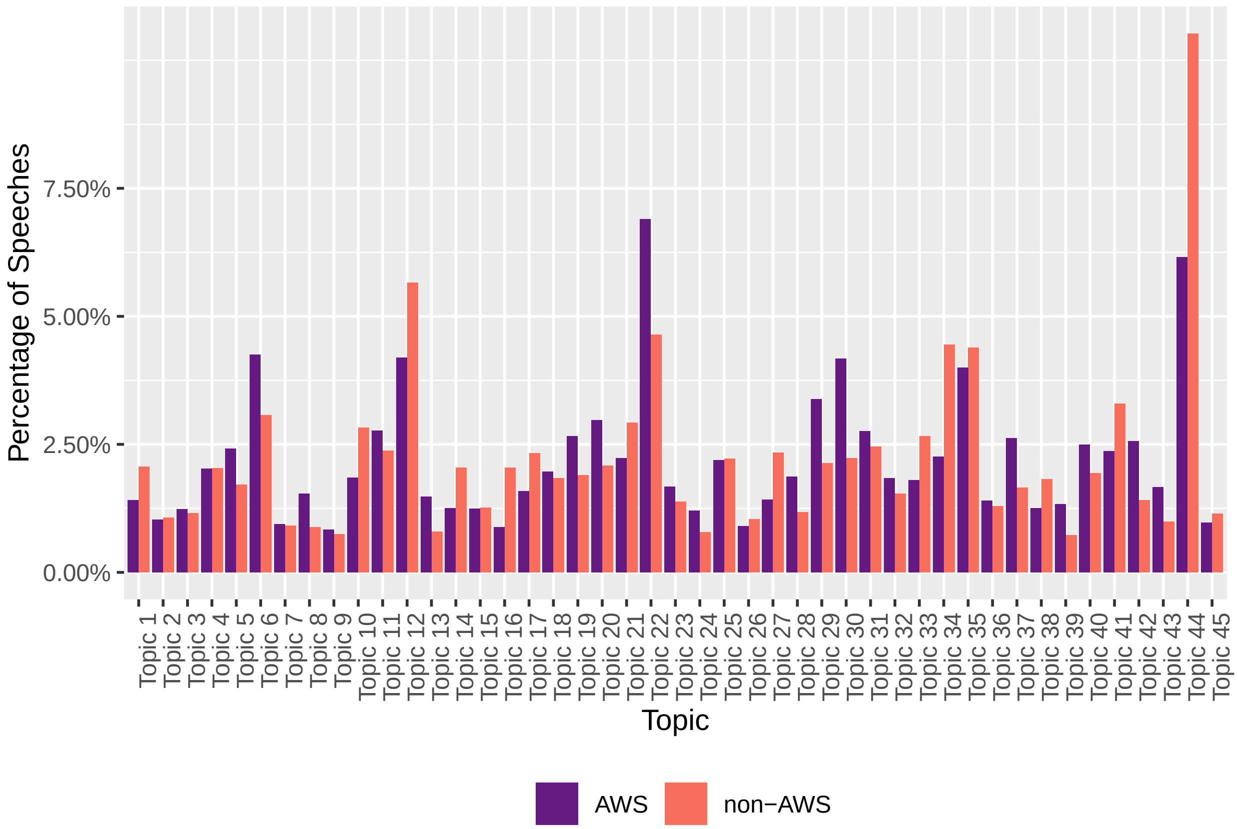

Figure 14: k45 Bar Chart

4.2.0.1 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 15: 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 15: 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 15: 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 15: 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 15: 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 15: 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

4.2.1 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, carpetrigh
##       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, @leamingtonsbc, @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, acquis, 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, visteon, 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
```

4.2.2 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)     0.0204893  0.0004321  47.418 < 0.0000000000000002 ***
## short_listTRUE -0.0027671  0.0005657  -4.891             0.000001 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 2:
##
## Coefficients:
##                   Estimate  Std. Error t value            Pr(>|t|)
## (Intercept)    0.011161637 0.000374994  29.765 <0.0000000000000002 ***
## short_listTRUE 0.000001093 0.000443614   0.002               0.998
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0181518  0.0003816  47.563 <0.0000000000000002 ***
## short_listTRUE 0.0010546  0.0004682   2.252              0.0243 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0188169  0.0005140  36.610 <0.0000000000000002 ***
## short_listTRUE -0.0002349  0.0006493  -0.362               0.718
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
```

```
## Topic 5:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0155152  0.0005330  29.109 < 0.0000000000000002 ***
## short_listTRUE 0.0041713  0.0006725   6.203       0.000000000557 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 6:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0369186  0.0003596 102.662 < 0.0000000000000002 ***
## short_listTRUE 0.0019887  0.0004484   4.436           0.00000919 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0193245  0.0002854  67.713 < 0.0000000000000002 ***
## short_listTRUE -0.0015244  0.0003413  -4.466           0.00000799 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 8:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0088858  0.0003885   22.87 <0.0000000000000002 ***
## short_listTRUE 0.0056204  0.0005576   10.08 <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)    0.0098236  0.0003671  26.760 <0.0000000000000002 ***
## short_listTRUE 0.0004845  0.0004456   1.087               0.277
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
```

```
## (Intercept)     0.0216349  0.0005611  38.561 < 0.0000000000000002 ***
## short_listTRUE -0.0047482  0.0006928  -6.853     0.00000000000726 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0315919  0.0004293  73.597 < 0.0000000000000002 ***
## short_listTRUE 0.0032102  0.0005290   6.068         0.0000000013 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 12:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0346260  0.0006983  49.587 < 0.0000000000000002 ***
## short_listTRUE -0.0072048  0.0009210  -7.823  0.00000000000000522 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0117041  0.0003656   32.02 <0.0000000000000002 ***
## short_listTRUE 0.0062183  0.0005028   12.37 <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)     0.0170284  0.0004597   37.04 < 0.0000000000000002 ***
## short_listTRUE -0.0032575  0.0006181   -5.27          0.000000137 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0166965  0.0003682  45.349 < 0.0000000000000002 ***
## short_listTRUE -0.0011879  0.0004417  -2.689              0.00716 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
##
## Topic 16:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0255023  0.0004347   58.67 <0.0000000000000002 ***
## short_listTRUE -0.0093016  0.0005047  -18.43 <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)     0.0259210  0.0004083   63.48 <0.0000000000000002 ***
## short_listTRUE -0.0055069  0.0005013  -10.98 <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)    0.0177190  0.0004539  39.041 <0.0000000000000002 ***
## short_listTRUE 0.0004196  0.0005417   0.775               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)    0.0165349  0.0005369  30.795 < 0.0000000000000002 ***
## short_listTRUE 0.0039398  0.0006550   6.015        0.00000000181 ***
## ---
## 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  0.0005797  31.284 < 0.0000000000000002 ***
## short_listTRUE 0.0038753  0.0006856   5.652         0.0000000159 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
```

```
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0240592  0.0006045  39.798 <0.0000000000000002 ***
## short_listTRUE -0.0062003  0.0007208  -8.602 <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)    0.0362028  0.0006392   56.64 <0.0000000000000002 ***
## short_listTRUE 0.0099866  0.0008292   12.04 <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)    0.0131318  0.0005666  23.176 <0.0000000000000002 ***
## short_listTRUE 0.0015190  0.0006445   2.357              0.0184 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0082626  0.0003712  22.260 <0.0000000000000002 ***
## short_listTRUE 0.0039105  0.0004615   8.474 <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)    0.0201314  0.0004705  42.787 <0.0000000000000002 ***
## short_listTRUE 0.0008757  0.0005716   1.532               0.126
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0117438  0.0003673  31.976 < 0.0000000000000002 ***
## short_listTRUE -0.0017163  0.0004546  -3.775              0.00016 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0214037  0.0004909   43.60 <0.0000000000000002 ***
## short_listTRUE -0.0059870  0.0005924  -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)    0.0143905  0.0004538  31.713 < 0.0000000000000002 ***
## short_listTRUE 0.0031474  0.0005608   5.612         0.0000000201 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0198815  0.0005673   35.05 <0.0000000000000002 ***
## short_listTRUE 0.0087584  0.0007003   12.51 <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)    0.0396925  0.0003949  100.52 <0.0000000000000002 ***
## short_listTRUE 0.0072002  0.0004861   14.81 <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)    0.0327931  0.0004276    76.7 <0.0000000000000002 ***
## short_listTRUE 0.0010250  0.0005396     1.9              0.0575 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
```

```
## Topic 32:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0267144  0.0003282  81.390 < 0.0000000000000002 ***
## short_listTRUE 0.0015694  0.0004104   3.824             0.000132 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 33:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0272250  0.0005545   49.10 <0.0000000000000002 ***
## short_listTRUE -0.0056724  0.0006410   -8.85 <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)     0.0323298  0.0005814   55.61 <0.0000000000000002 ***
## short_listTRUE -0.0127447  0.0007142  -17.84 <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)     0.0283372  0.0007007  40.440 <0.0000000000000002 ***
## short_listTRUE -0.0010485  0.0008674  -1.209               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)    0.0157197  0.0003773  41.666 < 0.0000000000000002 ***
## short_listTRUE 0.0015066  0.0004869   3.094              0.00197 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 37:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
```

```
## (Intercept)    0.0236864  0.0003805   62.25 <0.0000000000000002 ***
## short_listTRUE 0.0061900  0.0005027   12.31 <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)     0.0280920  0.0003811   73.71 <0.0000000000000002 ***
## short_listTRUE -0.0065546  0.0005160  -12.70 <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)    0.0109071  0.0003934  27.725 < 0.0000000000000002 ***
## short_listTRUE 0.0038188  0.0005037   7.582   0.0000000000000344 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 40:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0285255  0.0004147  68.781 <0.0000000000000002 ***
## short_listTRUE 0.0009304  0.0004730   1.967              0.0492 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 41:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0259797  0.0005469  47.502 < 0.0000000000000002 ***
## short_listTRUE -0.0052564  0.0006546  -8.029 0.000000000000000993 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 42:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0168738  0.0004256   39.65 <0.0000000000000002 ***
## short_listTRUE 0.0083551  0.0005728   14.59 <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)    0.0132706  0.0003984   33.31 <0.0000000000000002 ***
## short_listTRUE 0.0070789  0.0005334   13.27 <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)     0.0676847  0.0004198  161.23 <0.0000000000000002 ***
## short_listTRUE -0.0154109  0.0005219  -29.53 <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)     0.0168123  0.0003077  54.641 <0.0000000000000002 ***
## short_listTRUE -0.0005808  0.0003825  -1.519               0.129
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

4.3 K60

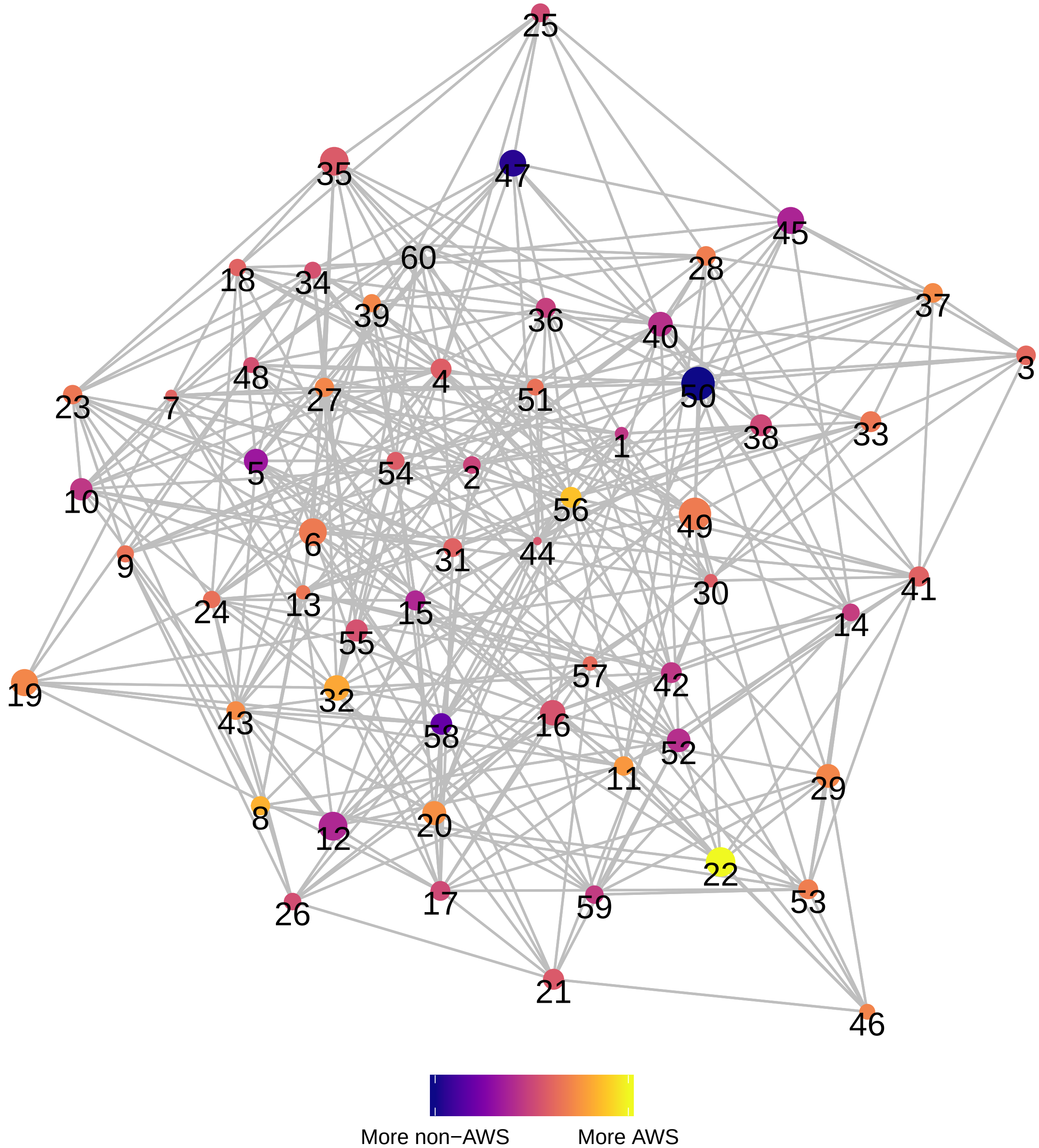

Figure 15: Fruchterman-Reingold plot of K60 Network

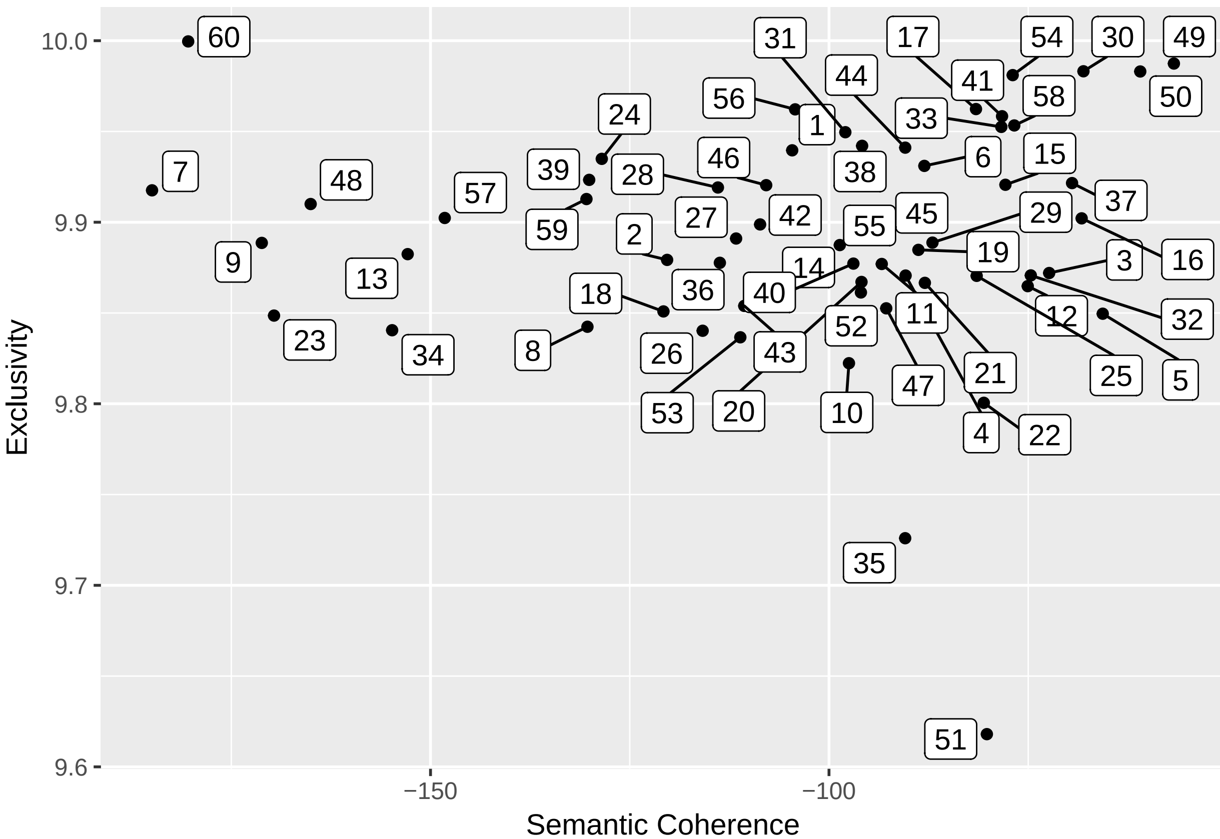

Figure 16: Coherence of K60 Topic Models

Table 16: 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%	1,390	0.82%
Topic 15	660	1.23%	440	1.58%	2,101	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 16: 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%	3,374	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%	7,672	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%	16,080	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%	2,570	1.52%
Topic 59	459	0.85%	411	1.48%	1,696	1%

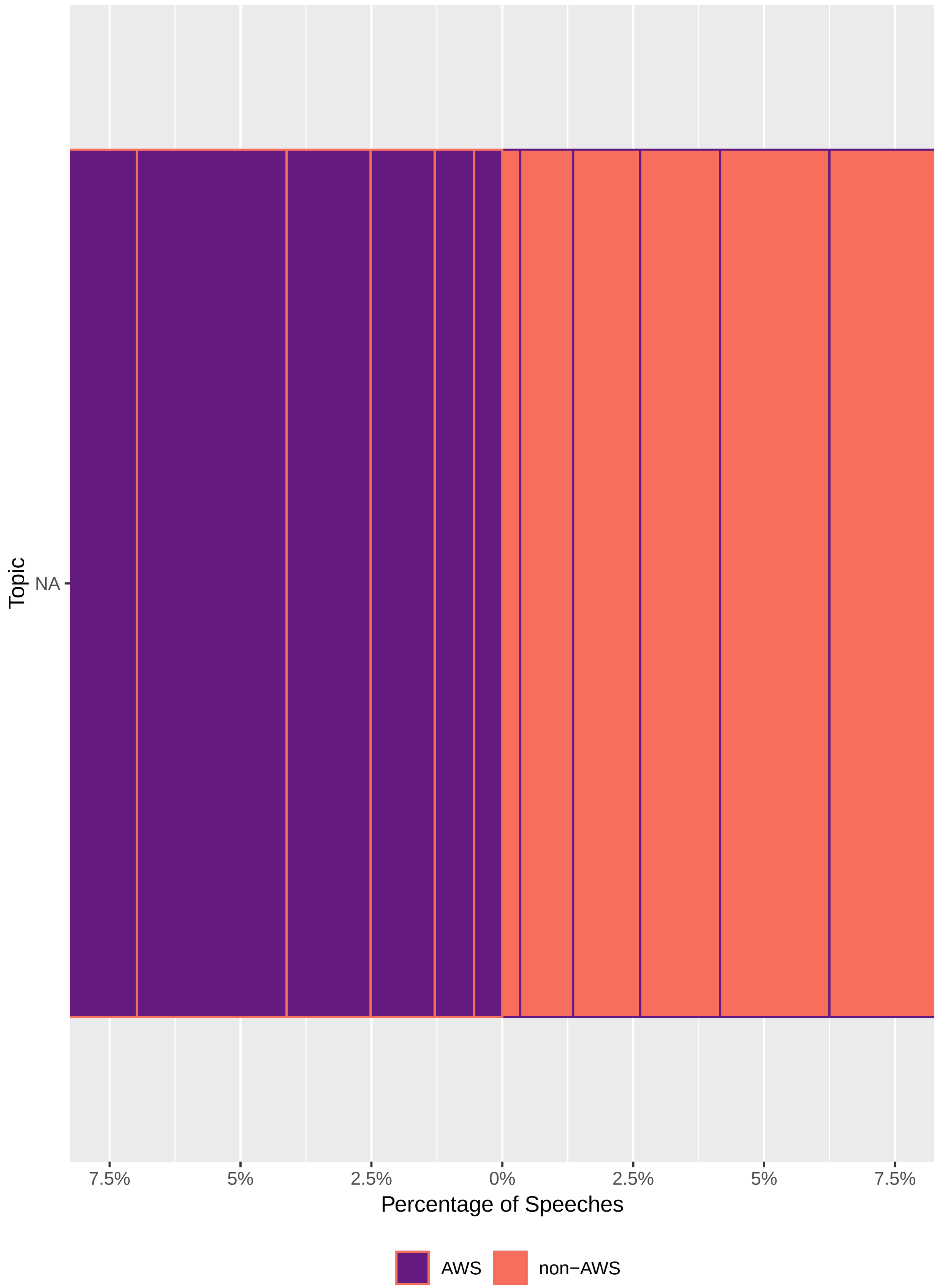

Figure 17: K60 Pyramid Chart

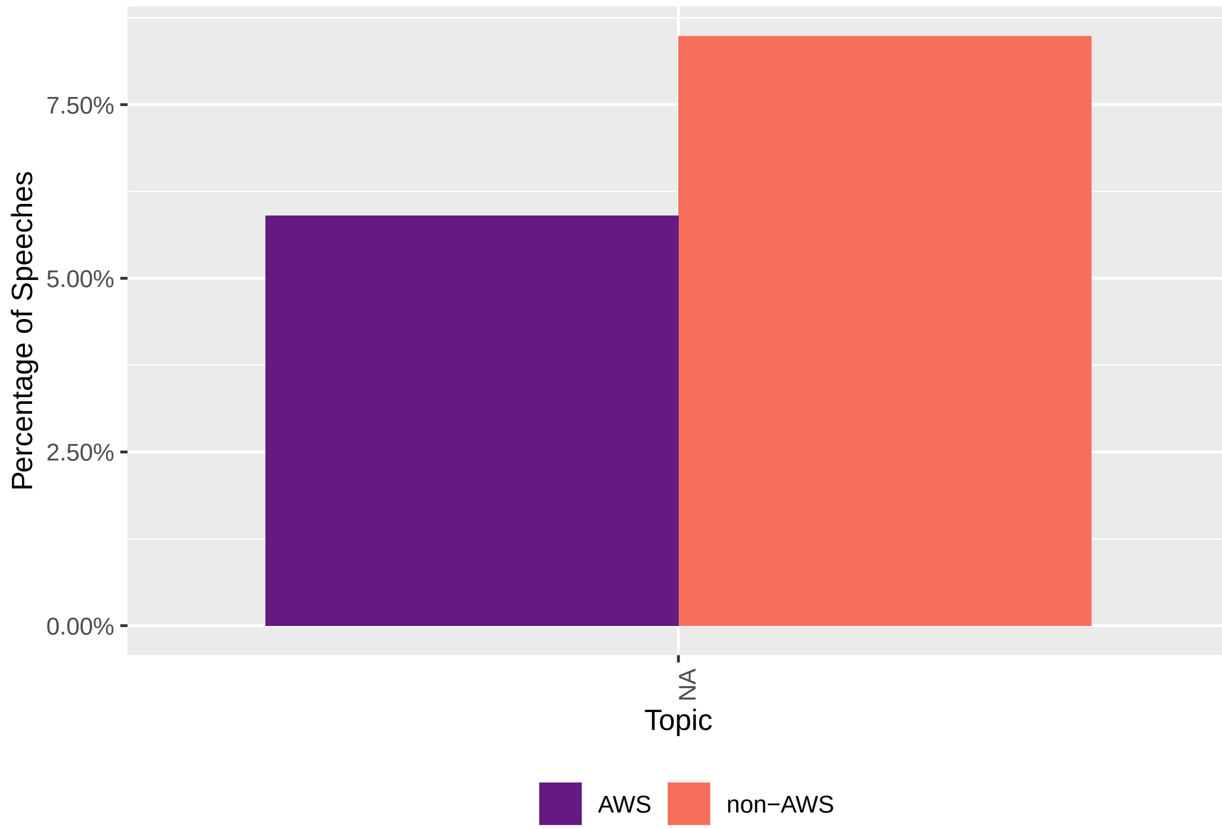

Figure 18: K60 Bar Chart

4.3.0.1 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 17: 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 17: 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, remploy, national, impaired, epilepsy, use, however	deaf, remploy, 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 17: 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, gcses, 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 17: 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 17: 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 17: 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 17: 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 17: 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

4.3.1 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, bucke
##       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
```

4.3.2 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)     0.0130364  0.0002920  44.643 <0.0000000000000002 ***
## short_listTRUE -0.0031240  0.0003378  -9.247 <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)     0.0121075  0.0003355  36.088 < 0.0000000000000002 ***
## short_listTRUE -0.0020891  0.0004261  -4.902          0.000000949 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0167125  0.0003705  45.106 <0.0000000000000002 ***
## short_listTRUE 0.0011201  0.0004237   2.644              0.0082 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0140785  0.0004865  28.940 <0.0000000000000002 ***
## short_listTRUE 0.0002098  0.0005622   0.373               0.709
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 5:
```

```
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0210680  0.0005079  41.482 <0.0000000000000002 ***
## short_listTRUE -0.0060120  0.0006144  -9.785 <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)    0.0256000  0.0004107  62.339 < 0.0000000000000002 ***
## short_listTRUE 0.0025381  0.0005359   4.736           0.00000218 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0039743  0.0001849  21.492 < 0.0000000000000002 ***
## short_listTRUE 0.0007519  0.0002308   3.258              0.00112 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 8:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0061455  0.0003473   17.70 <0.0000000000000002 ***
## short_listTRUE 0.0064992  0.0004842   13.42 <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)    0.0062910  0.0003190  19.720 < 0.0000000000000002 ***
## short_listTRUE 0.0020025  0.0003972   5.042          0.000000462 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0175490  0.0004541  38.645 < 0.0000000000000002 ***
```

```
## short_listTRUE -0.0031715  0.0005672  -5.591         0.0000000226 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0108576  0.0003303   32.87 <0.0000000000000002 ***
## short_listTRUE 0.0047538  0.0004006   11.87 <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)     0.0263239  0.0006127  42.967 < 0.0000000000000002 ***
## short_listTRUE -0.0045797  0.0007144  -6.411       0.000000000146 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0053938  0.0002636  20.458 < 0.0000000000000002 ***
## short_listTRUE 0.0022118  0.0003218   6.874      0.0000000000063 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0131828  0.0003546  37.181 < 0.0000000000000002 ***
## short_listTRUE -0.0025216  0.0004233  -5.957        0.00000000257 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0226973  0.0004319  52.556 <0.0000000000000002 ***
## short_listTRUE -0.0045705  0.0004749  -9.625 <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)     0.0218764  0.0004868  44.940 <0.0000000000000002 ***
## short_listTRUE -0.0006785  0.0005795  -1.171               0.242
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 17:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0203203  0.0003545  57.325 < 0.0000000000000002 ***
## short_listTRUE -0.0015014  0.0004208  -3.568              0.00036 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0089788  0.0003488  25.742 <0.0000000000000002 ***
## short_listTRUE 0.0006025  0.0004144   1.454               0.146
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 19:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0190534  0.0005340  35.683 < 0.0000000000000002 ***
## short_listTRUE 0.0035244  0.0006826   5.163          0.000000244 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0136496  0.0005000  27.301 < 0.0000000000000002 ***
## short_listTRUE 0.0042746  0.0006757   6.326       0.000000000253 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:
```

```
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)     0.0132540  0.0004108  32.260 <0.0000000000000002 ***
## short_listTRUE -0.0001370  0.0005174  -0.265               0.791
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 22:
##
## Coefficients:
##                Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0196781  0.0005845   33.67 <0.0000000000000002 ***
## short_listTRUE 0.0108699  0.0007200   15.10 <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)    0.0092183  0.0004264  21.617 < 0.0000000000000002 ***
## short_listTRUE 0.0023115  0.0005320   4.344            0.000014 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0075496  0.0003069  24.601 < 0.0000000000000002 ***
## short_listTRUE 0.0017449  0.0003611   4.831          0.00000136 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 25:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0131888  0.0004242  31.093 < 0.0000000000000002 ***
## short_listTRUE -0.0013556  0.0004858  -2.791             0.00526 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0103655  0.0003366  30.792 < 0.0000000000000002 ***
## short_listTRUE -0.0011202  0.0004333  -2.585             0.00973 **
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0116671  0.0003824  30.514 < 0.0000000000000002 ***
## short_listTRUE 0.0034901  0.0004539   7.689    0.000000000000015 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 28:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0109637  0.0003398  32.268 < 0.0000000000000002 ***
## short_listTRUE 0.0028701  0.0004093   7.013     0.00000000000236 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0170771  0.0004520  37.778 < 0.0000000000000002 ***
## short_listTRUE 0.0034784  0.0005885   5.911        0.00000000341 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 30:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0213890  0.0001861 114.941 <0.0000000000000002 ***
## short_listTRUE 0.0002539  0.0002444   1.039               0.299
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 31:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0208859  0.0003050  68.476 <0.0000000000000002 ***
## short_listTRUE 0.0005468  0.0003660   1.494               0.135
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 32:
```

```
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0196070  0.0004507   43.50 <0.0000000000000002 ***
## short_listTRUE 0.0058522  0.0005138   11.39 <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)    0.0154459  0.0003324  46.471 < 0.0000000000000002 ***
## short_listTRUE 0.0023258  0.0003855   6.034        0.00000000161 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 34:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0096916  0.0003729  25.987 <0.0000000000000002 ***
## short_listTRUE -0.0008210  0.0004533  -1.811              0.0701 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 35:
##
## Coefficients:
##                  Estimate  Std. Error t value            Pr(>|t|)
## (Intercept)     0.02396096  0.00062348   38.43 <0.0000000000000002 ***
## short_listTRUE -0.00004798  0.00079606   -0.06               0.952
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 36:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0160670  0.0004389  36.605 < 0.0000000000000002 ***
## short_listTRUE -0.0024391  0.0005374  -4.538           0.00000568 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 37:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0168671  0.0002535   66.53 <0.0000000000000002 ***
```

```
## short_listTRUE 0.0037580  0.0003250   11.56 <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)     0.0239576  0.0003851  62.211 < 0.0000000000000002 ***
## short_listTRUE -0.0016716  0.0004757  -3.514             0.000442 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 39:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0075329  0.0003341  22.548 <0.0000000000000002 ***
## short_listTRUE 0.0035186  0.0003947   8.915 <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)     0.0220747  0.0004830  45.706 < 0.0000000000000002 ***
## short_listTRUE -0.0036849  0.0005528  -6.665      0.0000000000266 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 41:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0246499  0.0002837  86.874 <0.0000000000000002 ***
## short_listTRUE 0.0005342  0.0003644   1.466               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)     0.0176328  0.0004563  38.643 < 0.0000000000000002 ***
## short_listTRUE -0.0031292  0.0005328  -5.874       0.00000000428 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
##
## Topic 43:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0117521  0.0004170  28.184 < 0.0000000000000002 ***
## short_listTRUE 0.0038075  0.0005176   7.356    0.000000000000191 ***
## ---
## 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  0.0001374  66.645 < 0.0000000000000002 ***
## short_listTRUE -0.0004898  0.0001664  -2.943              0.00325 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 45:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0318785  0.0006193  51.476 < 0.0000000000000002 ***
## short_listTRUE -0.0048648  0.0007511  -6.477      0.0000000000941 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 46:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0066541  0.0002701  24.640 <0.0000000000000002 ***
## short_listTRUE 0.0033241  0.0003490   9.524 <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)     0.0307960  0.0005901   52.19 <0.0000000000000002 ***
## short_listTRUE -0.0133641  0.0007683  -17.39 <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)     0.0086561  0.0003023   28.63 < 0.0000000000000002 ***
## short_listTRUE -0.0010012  0.0003694   -2.71              0.00672 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 49:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0438292  0.0003998 109.626 < 0.0000000000000002 ***
## short_listTRUE 0.0026581  0.0004707   5.647         0.0000000164 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 50:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0557464  0.0003495  159.50 <0.0000000000000002 ***
## short_listTRUE -0.0144744  0.0004284  -33.79 <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)    0.0098988  0.0003692  26.809 < 0.0000000000000002 ***
## short_listTRUE 0.0017971  0.0004673   3.846              0.00012 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 52:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0184075  0.0005253  35.041 < 0.0000000000000002 ***
## short_listTRUE -0.0039554  0.0006825  -5.796        0.00000000683 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 53:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0110252  0.0003795  29.051 < 0.0000000000000002 ***
## short_listTRUE 0.0028328  0.0004673   6.063        0.00000000135 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 54:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0266571  0.0002023  131.75 <0.0000000000000002 ***
## short_listTRUE 0.0001332  0.0002514    0.53               0.596
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 55:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0174608  0.0004907  35.585 <0.0000000000000002 ***
## short_listTRUE -0.0008271  0.0005885  -1.405                0.16
## ---
## 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  0.0003134   52.87 <0.0000000000000002 ***
## short_listTRUE 0.0075485  0.0004004   18.85 <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)    0.0066538  0.0002806  23.713 < 0.0000000000000002 ***
## short_listTRUE 0.0014067  0.0003397   4.141            0.0000347 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 58:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0270027  0.0003685   73.28 <0.0000000000000002 ***
## short_listTRUE -0.0097559  0.0004496  -21.70 <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)     0.0124008  0.0003522  35.205 < 0.0000000000000002 ***
## short_listTRUE -0.0027907  0.0004023  -6.937     0.00000000000403 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 60:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.00382593 0.00003701  103.38 <0.0000000000000002 ***
## short_listTRUE 0.00064376 0.00004646   13.86 <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 20).

There are several clusters of topics in 19. 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

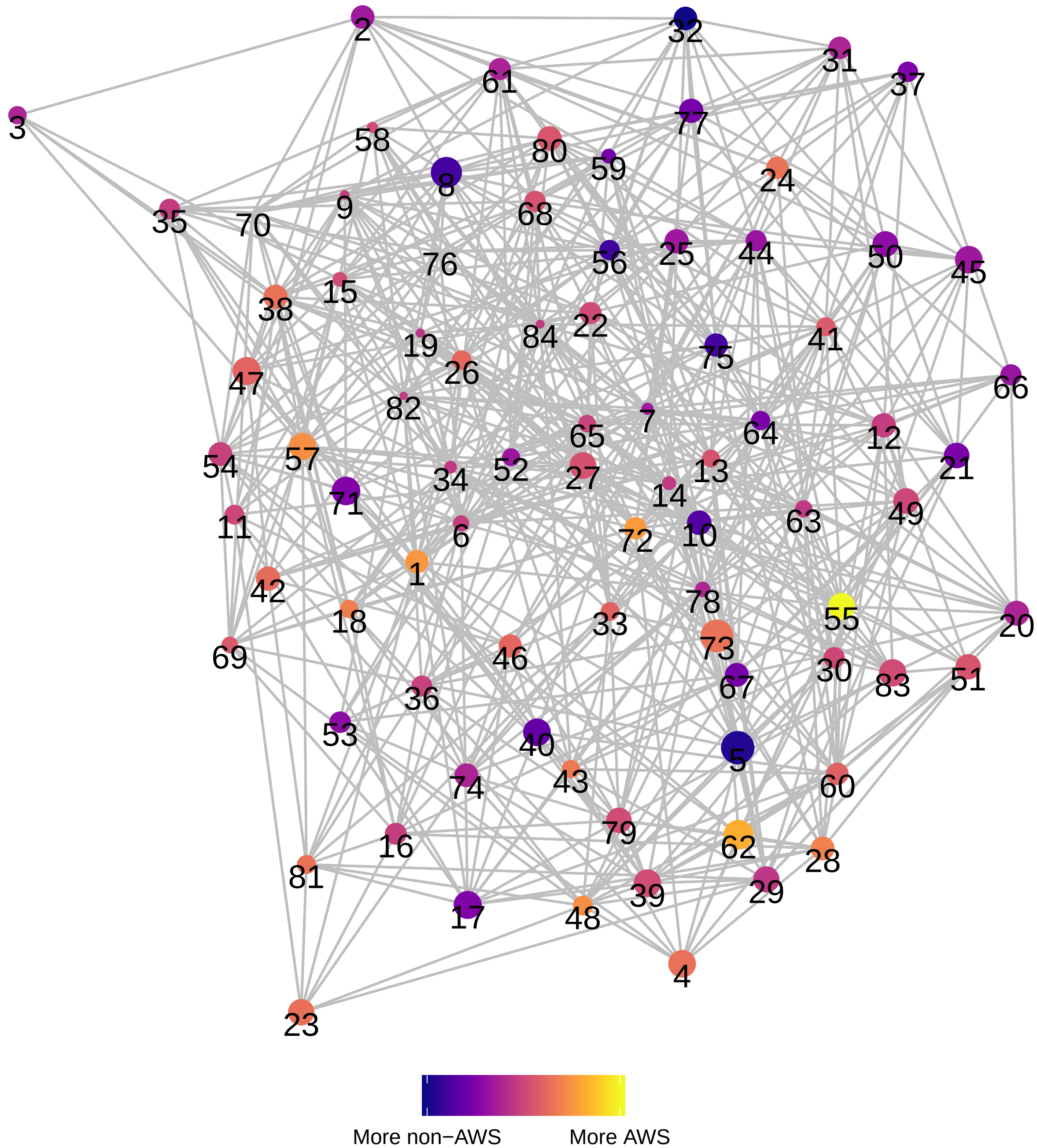

Figure 19: Fruchterman-Reingold plot of k0 Network

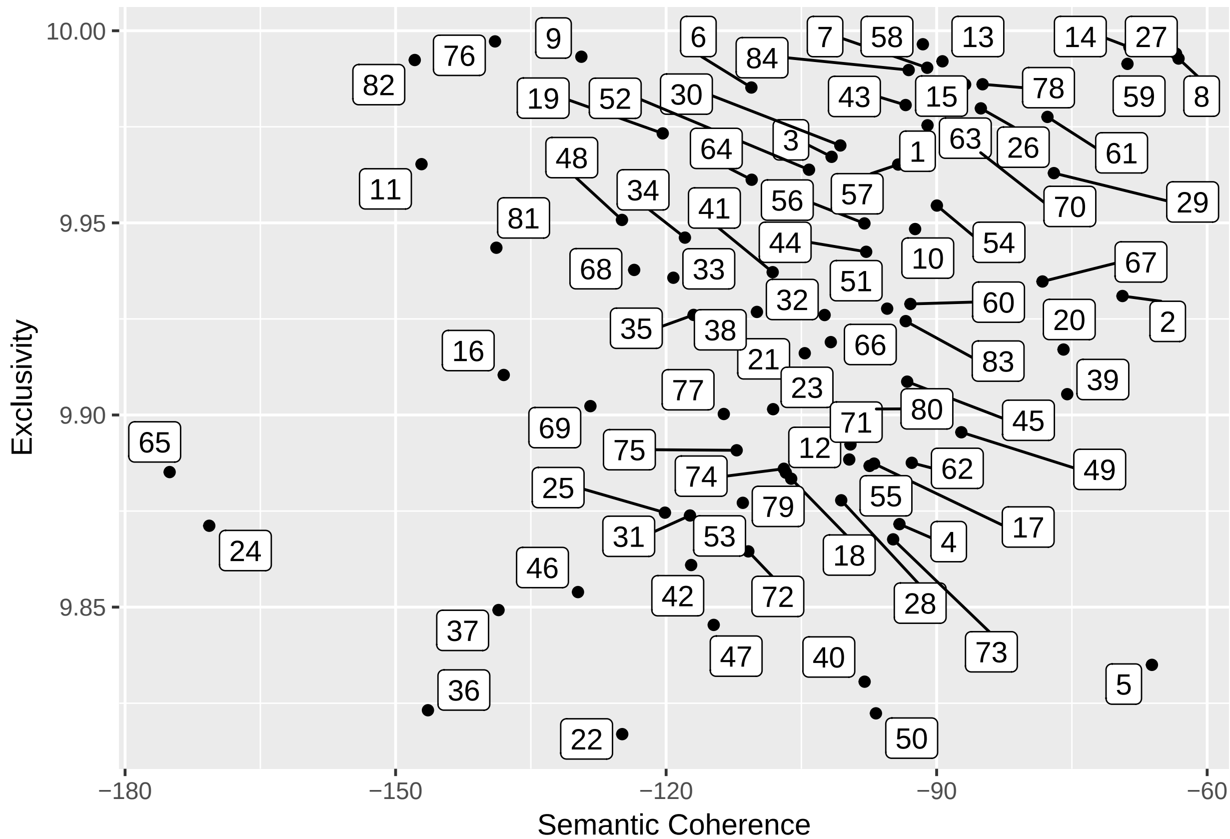

Figure 20: Coherence of k0 Topic Models

Table 18: 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%	NA	NA%
Topic 2	699	1.3%	397	1.42%	NA	NA%
Topic 3	264	0.49%	218	0.78%	NA	NA%
Topic 4	1,255	2.33%	506	1.82%	NA	NA%
Topic 5	1,601	2.98%	1,342	4.82%	NA	NA%
Topic 6	218	0.41%	74	0.27%	NA	NA%
Topic 7	45	0.08%	25	0.09%	NA	NA%
Topic 8	1,287	2.39%	1,142	4.1%	NA	NA%
Topic 9	10	0.02%	2	0.01%	NA	NA%
Topic 10	699	1.3%	527	1.89%	NA	NA%
Topic 11	421	0.78%	202	0.72%	NA	NA%
Topic 12	744	1.38%	440	1.58%	NA	NA%
Topic 13	341	0.63%	97	0.35%	NA	NA%
Topic 14	98	0.18%	54	0.19%	NA	NA%
Topic 15	138	0.26%	57	0.2%	NA	NA%
Topic 16	538	1%	331	1.19%	NA	NA%
Topic 17	1,023	1.9%	801	2.87%	NA	NA%

Table 18: 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%	NA	NA%
Topic 19	5	0.01%	2	0.01%	NA	NA%
Topic 20	848	1.58%	469	1.68%	NA	NA%
Topic 21	832	1.55%	573	2.06%	NA	NA%
Topic 22	611	1.14%	283	1.02%	NA	NA%
Topic 23	1,125	2.09%	414	1.49%	NA	NA%
Topic 24	687	1.28%	236	0.85%	NA	NA%
Topic 25	743	1.38%	465	1.67%	NA	NA%
Topic 26	462	0.86%	144	0.52%	NA	NA%
Topic 27	1,183	2.2%	435	1.56%	NA	NA%
Topic 28	876	1.63%	254	0.91%	NA	NA%
Topic 29	1,013	1.88%	484	1.74%	NA	NA%
Topic 30	523	0.97%	275	0.99%	NA	NA%
Topic 31	582	1.08%	367	1.32%	NA	NA%
Topic 32	460	0.86%	639	2.29%	NA	NA%
Topic 33	417	0.78%	109	0.39%	NA	NA%
Topic 34	61	0.11%	31	0.11%	NA	NA%
Topic 35	506	0.94%	242	0.87%	NA	NA%
Topic 36	490	0.91%	272	0.98%	NA	NA%
Topic 37	346	0.64%	347	1.25%	NA	NA%
Topic 38	915	1.7%	279	1%	NA	NA%
Topic 39	1,149	2.14%	582	2.09%	NA	NA%
Topic 40	974	1.81%	780	2.8%	NA	NA%
Topic 41	434	0.81%	109	0.39%	NA	NA%
Topic 42	884	1.64%	331	1.19%	NA	NA%
Topic 43	363	0.67%	105	0.38%	NA	NA%
Topic 44	452	0.84%	316	1.13%	NA	NA%
Topic 45	1,103	2.05%	633	2.27%	NA	NA%
Topic 46	756	1.41%	285	1.02%	NA	NA%
Topic 47	1,291	2.4%	544	1.95%	NA	NA%
Topic 48	514	0.96%	129	0.46%	NA	NA%
Topic 49	932	1.73%	489	1.76%	NA	NA%
Topic 50	848	1.58%	592	2.12%	NA	NA%
Topic 51	953	1.77%	425	1.53%	NA	NA%
Topic 52	275	0.51%	161	0.58%	NA	NA%
Topic 53	474	0.88%	349	1.25%	NA	NA%
Topic 54	774	1.44%	363	1.3%	NA	NA%
Topic 55	1,429	2.66%	208	0.75%	NA	NA%
Topic 56	263	0.49%	438	1.57%	NA	NA%
Topic 57	1,314	2.44%	328	1.18%	NA	NA%
Topic 58	40	0.07%	NA	NA%	NA	NA%
Topic 59	113	0.21%	88	0.32%	NA	NA%
Topic 60	676	1.26%	251	0.9%	NA	NA%
Topic 61	555	1.03%	351	1.26%	NA	NA%

Table 18: 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%	NA	NA%
Topic 63	242	0.45%	144	0.52%	NA	NA%
Topic 64	308	0.57%	261	0.94%	NA	NA%
Topic 65	300	0.56%	113	0.41%	NA	NA%
Topic 66	465	0.86%	325	1.17%	NA	NA%
Topic 67	616	1.15%	509	1.83%	NA	NA%
Topic 68	541	1.01%	246	0.88%	NA	NA%
Topic 69	225	0.42%	102	0.37%	NA	NA%
Topic 71	1,143	2.13%	779	2.8%	NA	NA%
Topic 72	726	1.35%	200	0.72%	NA	NA%
Topic 73	1,974	3.67%	827	2.97%	NA	NA%
Topic 74	704	1.31%	426	1.53%	NA	NA%
Topic 75	523	0.97%	540	1.94%	NA	NA%
Topic 77	675	1.25%	517	1.86%	NA	NA%
Topic 78	160	0.3%	75	0.27%	NA	NA%
Topic 79	982	1.83%	415	1.49%	NA	NA%
Topic 80	903	1.68%	328	1.18%	NA	NA%
Topic 81	434	0.81%	99	0.36%	NA	NA%
Topic 82	2	0%	1	0%	NA	NA%
Topic 83	1,172	2.18%	525	1.88%	NA	NA%
Topic 84	NA	NA%	5	0.02%	NA	NA%
NA	255	0.47%	132	0.47%	169,341	100%

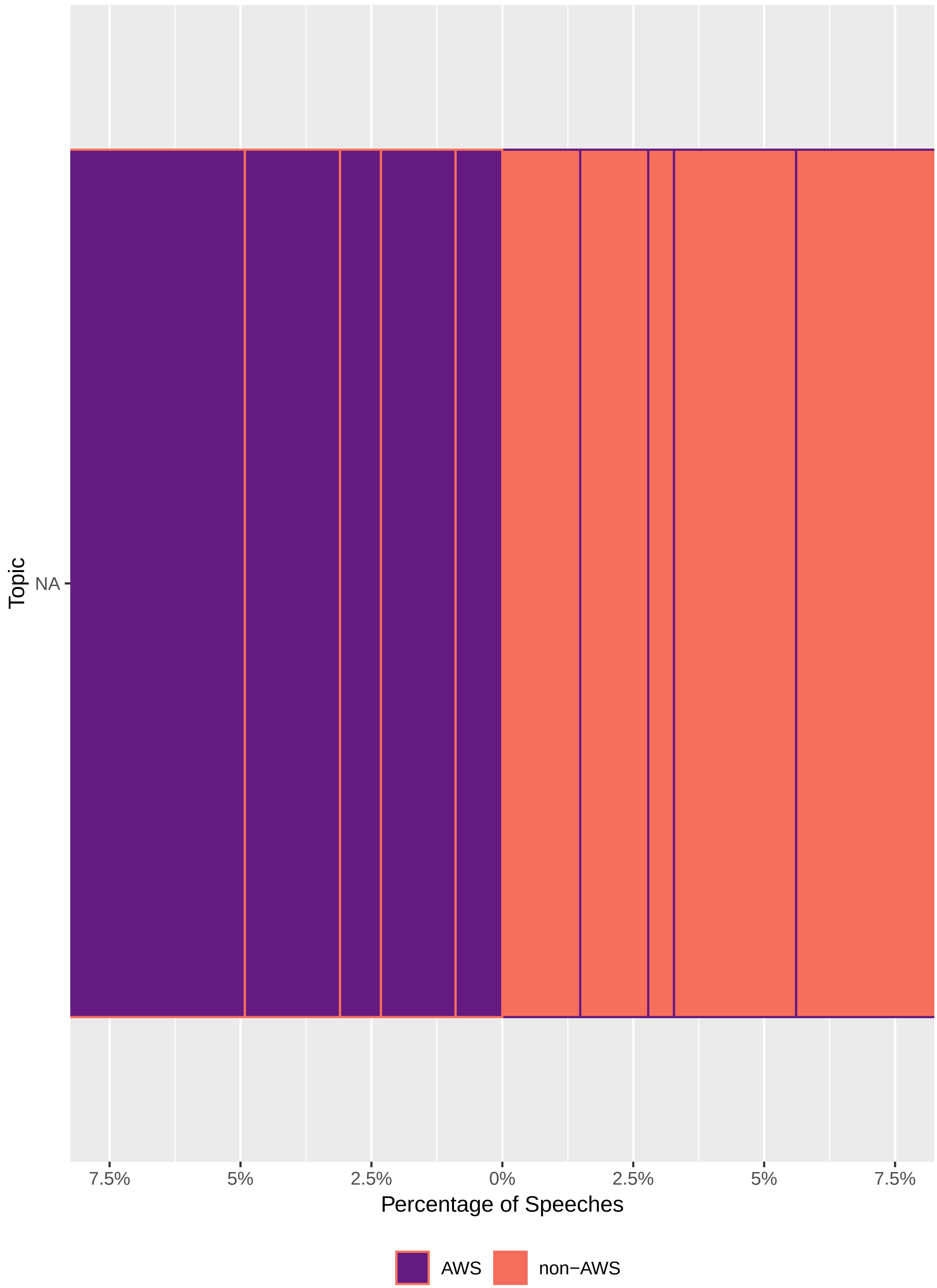

Figure 21: k0 Pyramid Chart

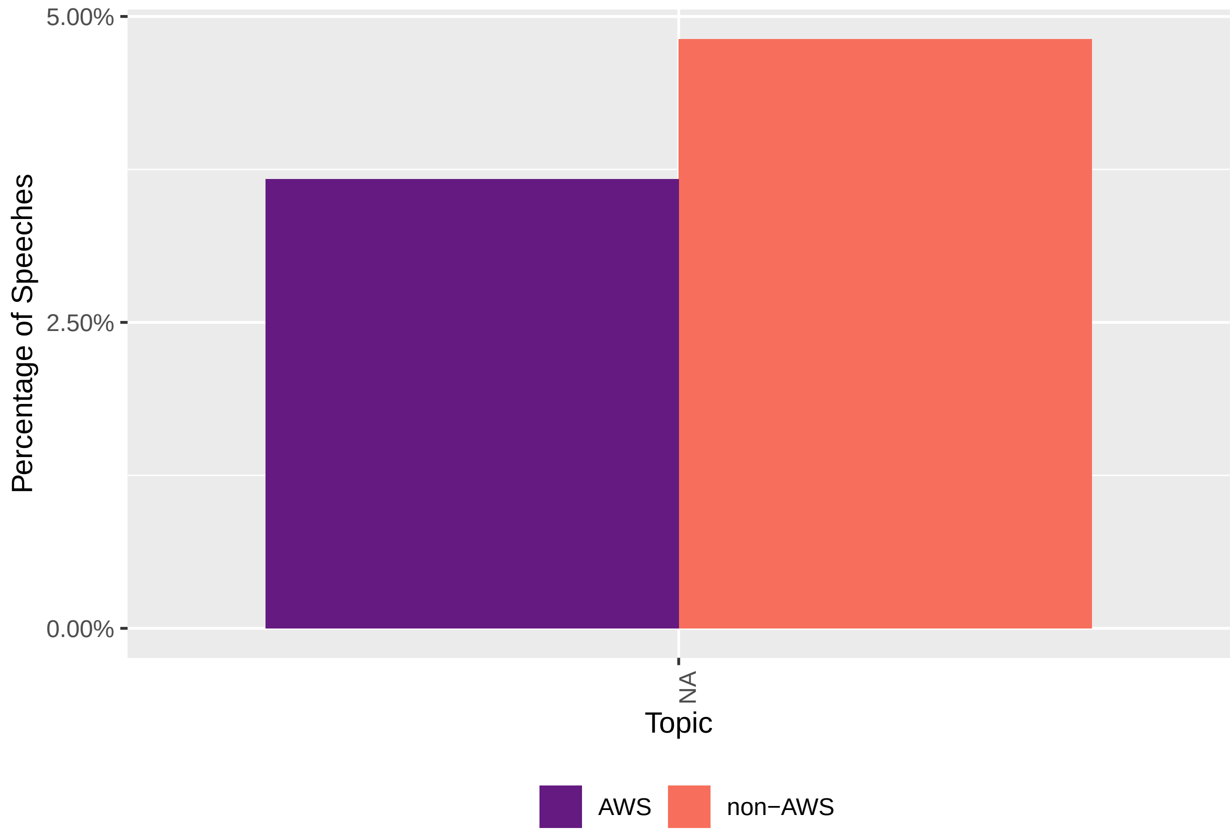

Figure 22: k0 Bar Chart

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 19: 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 19: 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 19: 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 19: 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 19: 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 19: 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, cancun, 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 19: 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 19: 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 19: 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, gcses, 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 19: 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, remploy
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

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## 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, cancun
##       Lift: cancun, 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, 0º, 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, gcses, pupils
##       Lift: apostrophe, headteachers, academisation, gcses, 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)    0.0128868  0.0002404    53.6 <0.0000000000000002 ***
## short_listTRUE 0.0048987  0.0002881    17.0 <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)     0.0147958  0.0004171   35.48 < 0.0000000000000002 ***
## short_listTRUE -0.0018860  0.0005084   -3.71             0.000208 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0082673  0.0002428  34.046 < 0.0000000000000002 ***
## short_listTRUE -0.0012073  0.0003075  -3.927            0.0000862 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0117261  0.0004621   25.38 < 0.0000000000000002 ***
## short_listTRUE 0.0030507  0.0005745    5.31           0.00000011 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 5:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0237256  0.0006266  37.865 <0.0000000000000002 ***
## short_listTRUE -0.0069861  0.0007804  -8.952 <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)    0.0086983  0.0000969  89.766 <0.0000000000000002 ***
## short_listTRUE 0.0002345  0.0001200   1.954              0.0507 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0152448  0.0001149   132.7 <0.0000000000000002 ***
## short_listTRUE -0.0019491  0.0001412   -13.8 <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)     0.0295340  0.0002210  133.65 <0.0000000000000002 ***
## short_listTRUE -0.0057617  0.0002618  -22.01 <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)    0.00668294 0.00006618 100.984 < 0.0000000000000002 ***
## short_listTRUE 0.00022463 0.00007575   2.965              0.00302 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0196198  0.0003416   57.44 <0.0000000000000002 ***
## short_listTRUE -0.0051510  0.0004200  -12.27 <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)    0.0055835  0.0002829  19.740 <0.0000000000000002 ***
## short_listTRUE 0.0006480  0.0003635   1.783              0.0747 .
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 12:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0110057  0.0003903  28.195 <0.0000000000000002 ***
## short_listTRUE 0.0001719  0.0004860   0.354               0.724
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0104917  0.0001347  77.869 <0.0000000000000002 ***
## short_listTRUE 0.0013426  0.0001628   8.249 <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)     0.01296631  0.00012582 103.052 <0.0000000000000002 ***
## short_listTRUE -0.00007094  0.00015844  -0.448               0.654
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0104986  0.0001058  99.242 < 0.0000000000000002 ***
## short_listTRUE 0.0010409  0.0001334   7.803  0.00000000000000613 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 16:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0092004  0.0003676  25.030 <0.0000000000000002 ***
## short_listTRUE 0.0002048  0.0004368   0.469               0.639
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
```

```
## Topic 17:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0154863  0.0004342  35.666 < 0.0000000000000002 ***
## short_listTRUE -0.0032977  0.0005525  -5.968        0.00000000241 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0079823  0.0002049   38.95 <0.0000000000000002 ***
## short_listTRUE 0.0036787  0.0002572   14.30 <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)     0.00579654  0.00007786  74.448 < 0.0000000000000002 ***
## short_listTRUE -0.00029251  0.00008329  -3.512             0.000445 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0137656  0.0003536  38.935 < 0.0000000000000002 ***
## short_listTRUE -0.0012446  0.0004298  -2.896              0.00378 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0149488  0.0004932  30.312 < 0.0000000000000002 ***
## short_listTRUE -0.0036376  0.0006031  -6.032        0.00000000163 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 22:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
```

```
## (Intercept)    0.0084308  0.0003495  24.120 <0.0000000000000002 ***
## short_listTRUE 0.0009392  0.0004378   2.145             0.0319 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 23:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0107236  0.0004867  22.033 < 0.0000000000000002 ***
## short_listTRUE 0.0029654  0.0005642   5.256          0.000000148 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0068210  0.0003517  19.393 < 0.0000000000000002 ***
## short_listTRUE 0.0031777  0.0004629   6.864     0.00000000000673 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 25:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0124830  0.0004129  30.231 < 0.0000000000000002 ***
## short_listTRUE -0.0019807  0.0005247  -3.775              0.00016 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0171435  0.0001816   94.39 <0.0000000000000002 ***
## short_listTRUE 0.0025509  0.0002258   11.30 <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)    0.0237719  0.0001783 133.294 < 0.0000000000000002 ***
## short_listTRUE 0.0013251  0.0002266   5.848        0.00000000499 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
##
## Topic 28:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0091592  0.0003799  24.109 < 0.0000000000000002 ***
## short_listTRUE 0.0039057  0.0004773   8.183 0.000000000000000281 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0185891  0.0003325   55.91 <0.0000000000000002 ***
## short_listTRUE -0.0001891  0.0003938   -0.48               0.631
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 30:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0162151  0.0002557  63.415 <0.0000000000000002 ***
## short_listTRUE 0.0007074  0.0003005   2.354              0.0186 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 31:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0097978  0.0003474  28.200 < 0.0000000000000002 ***
## short_listTRUE -0.0012503  0.0004199  -2.977              0.00291 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 32:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0175113  0.0004022   43.54 <0.0000000000000002 ***
## short_listTRUE -0.0075549  0.0004408  -17.14 <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)    0.0048046  0.0002583  18.599 < 0.0000000000000002 ***
## short_listTRUE 0.0022693  0.0003212   7.065     0.00000000000162 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 34:
##
## Coefficients:
##                  Estimate  Std. Error t value            Pr(>|t|)
## (Intercept)     0.00528910  0.00009011  58.694 <0.0000000000000002 ***
## short_listTRUE -0.00014693  0.00010948  -1.342                0.18
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 35:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0083637  0.0003056  27.364 <0.0000000000000002 ***
## short_listTRUE 0.0001034  0.0003905   0.265               0.791
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 36:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0078620  0.0002966  26.505 <0.0000000000000002 ***
## short_listTRUE 0.0003433  0.0003895   0.882               0.378
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 37:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0102557  0.0003845  26.672 < 0.0000000000000002 ***
## short_listTRUE -0.0034073  0.0004528  -7.525   0.0000000000000533 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 38:
##
## Coefficients:
##                Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.009796   0.000370  26.476 < 0.0000000000000002 ***
## short_listTRUE 0.003034   0.000441   6.881     0.00000000000597 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 39:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0148472  0.0003738  39.724 <0.0000000000000002 ***
## short_listTRUE 0.0010620  0.0004523   2.348              0.0189 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 40:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0171993  0.0005027  34.215 < 0.0000000000000002 ***
## short_listTRUE -0.0045034  0.0005697  -7.904  0.00000000000000273 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 41:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0068718  0.0002437  28.202 < 0.0000000000000002 ***
## short_listTRUE 0.0018013  0.0003201   5.628         0.0000000183 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 42:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0086560  0.0004131   20.95 < 0.0000000000000002 ***
## short_listTRUE 0.0027439  0.0005237    5.24          0.000000161 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 43:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0137496  0.0001735   79.27 <0.0000000000000002 ***
## short_listTRUE 0.0034618  0.0002288   15.13 <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)     0.0148523  0.0002927   50.75 < 0.0000000000000002 ***
## short_listTRUE -0.0022465  0.0003129   -7.18    0.000000000000704 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 45:
##
## Coefficients:
##                   Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0141168  0.0004758  29.669 < 0.0000000000000002 ***
## short_listTRUE -0.0019764  0.0005784  -3.417             0.000633 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 46:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0081247  0.0003813  21.306 < 0.0000000000000002 ***
## short_listTRUE 0.0025004  0.0005147   4.858           0.00000119 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 47:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0137946  0.0005355  25.762 < 0.0000000000000002 ***
## short_listTRUE 0.0023402  0.0006459   3.623             0.000291 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 48:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0068209  0.0002311   29.52 <0.0000000000000002 ***
## short_listTRUE 0.0045037  0.0003254   13.84 <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)    0.0128967  0.0003693  34.924 <0.0000000000000002 ***
## short_listTRUE 0.0006853  0.0004741   1.445              0.148
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 50:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0134248  0.0004223  31.789 < 0.0000000000000002 ***
## short_listTRUE -0.0026429  0.0004826  -5.477         0.0000000435 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 51:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0116050  0.0003947  29.404 < 0.0000000000000002 ***
## short_listTRUE 0.0015190  0.0005040   3.014              0.00258 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 52:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0121926  0.0002008  60.712 <0.0000000000000002 ***
## short_listTRUE -0.0021457  0.0002388  -8.987 <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)     0.0107991  0.0003210  33.643 < 0.0000000000000002 ***
## short_listTRUE -0.0027914  0.0003884  -7.188    0.000000000000665 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 54:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0153546  0.0002297  66.852 <0.0000000000000002 ***
## short_listTRUE 0.0003763  0.0002823   1.333               0.182
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
##
## Topic 55:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0081979  0.0003612   22.70 <0.0000000000000002 ***
## short_listTRUE 0.0089388  0.0004648   19.23 <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)     0.0171033  0.0002405   71.12 <0.0000000000000002 ***
## short_listTRUE -0.0060436  0.0002949  -20.50 <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)    0.0134735  0.0002544   52.97 <0.0000000000000002 ***
## short_listTRUE 0.0045553  0.0003287   13.86 <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)    0.00871667 0.00006390  136.42 <0.0000000000000002 ***
## short_listTRUE 0.00103216 0.00008243   12.52 <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)     0.0189672  0.0001364  139.09 <0.0000000000000002 ***
## short_listTRUE -0.0038774  0.0001716  -22.59 <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)    0.0111273  0.0003226  34.495 < 0.0000000000000002 ***
## short_listTRUE 0.0021739  0.0004257   5.107          0.000000328 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 61:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0153785  0.0002698  56.992 < 0.0000000000000002 ***
## short_listTRUE -0.0013741  0.0003477  -3.952            0.0000777 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 62:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0140869  0.0004657  30.248 <0.0000000000000002 ***
## short_listTRUE 0.0059402  0.0006560   9.056 <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)     0.01290515  0.00016850   76.59 <0.0000000000000002 ***
## short_listTRUE -0.00009767  0.00020797   -0.47               0.639
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 64:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0146829  0.0002485   59.09 <0.0000000000000002 ***
## short_listTRUE -0.0035580  0.0002914  -12.21 <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)    0.0051129  0.0002223  23.004 <0.0000000000000002 ***
## short_listTRUE 0.0005172  0.0002747   1.883              0.0598 .
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 66:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0095103  0.0003492  27.231 < 0.0000000000000002 ***
## short_listTRUE -0.0022143  0.0004253  -5.206          0.000000193 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 67:
##
## Coefficients:
##                  Estimate Std. Error t value           Pr(>|t|)
## (Intercept)     0.0157435  0.0002884   54.59 <0.0000000000000002 ***
## short_listTRUE -0.0038382  0.0003567  -10.76 <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)    0.0079498  0.0002806  28.330 < 0.0000000000000002 ***
## short_listTRUE 0.0013706  0.0003474   3.946            0.0000796 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 69:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0051651  0.0002140  24.132 < 0.0000000000000002 ***
## short_listTRUE 0.0017666  0.0002812   6.282       0.000000000336 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 70:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0103980  0.0001834  56.689 <0.0000000000000002 ***
## short_listTRUE 0.0002382  0.0002262   1.053               0.292
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
```

```
## Topic 71:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0171787  0.0004717  36.415 < 0.0000000000000002 ***
## short_listTRUE -0.0033313  0.0005507  -6.049        0.00000000146 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 72:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0084253  0.0003823   22.04 <0.0000000000000002 ***
## short_listTRUE 0.0050658  0.0004713   10.75 <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)    0.0166796  0.0005182  32.187 < 0.0000000000000002 ***
## short_listTRUE 0.0031393  0.0006412   4.896          0.000000981 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 74:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0121505  0.0003689  32.939 < 0.0000000000000002 ***
## short_listTRUE -0.0012786  0.0004694  -2.724              0.00645 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 75:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0161748  0.0003977   40.67 <0.0000000000000002 ***
## short_listTRUE -0.0058993  0.0004578  -12.89 <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)     0.00394180  0.00003248  121.37 <0.0000000000000002 ***
## short_listTRUE -0.00054610  0.00003826  -14.27 <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)     0.0140345  0.0003400  41.282 <0.0000000000000002 ***
## short_listTRUE -0.0037133  0.0004013  -9.254 <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)     0.0117274  0.0001143  102.59 <0.0000000000000002 ***
## short_listTRUE -0.0011795  0.0001411   -8.36 <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)    0.0128104  0.0004360  29.380 <0.0000000000000002 ***
## short_listTRUE 0.0009672  0.0005177   1.868              0.0617 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 80:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0136259  0.0003383  40.283 < 0.0000000000000002 ***
## short_listTRUE 0.0015574  0.0004262   3.654             0.000258 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 81:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0035173  0.0002134   16.48 <0.0000000000000002 ***
## short_listTRUE 0.0030901  0.0002616   11.81 <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)    0.00308529 0.00002982 103.449 < 0.0000000000000002 ***
## short_listTRUE 0.00010022 0.00003664   2.735             0.00623 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 83:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0147544  0.0003345   44.11 <0.0000000000000002 ***
## short_listTRUE 0.0009656  0.0004470    2.16             0.0308 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 84:
##
## Coefficients:
##                   Estimate  Std. Error t value           Pr(>|t|)
## (Intercept)    0.002165717 0.000020661 104.822 <0.0000000000000002 ***
## short_listTRUE 0.000002556 0.000023612   0.108              0.914
## ---
## 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 20: A random sample of KWIC's

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

Table 20: 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 Aldercar 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 20: 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 north-east Derbyshire and dentists in	my constituency	to find a local solution . These reforms coincide with
Cross , just a few miles up the road from	my constituency	. That pipe manufacturing works has been taken over by
go ahead . There is huge concern about this in	my constituency	and across the north . Was the Prime Minister told
backgrounds , including poor backgrounds , and is representative of	my constituency	. That is the sort of school that Labour Members
are subject to a TPIM . This information would let	my constituents	know whether potential terrorism suspects had returned to London .
. Gentleman for his generosity . Is he aware that	my constituency	is probably the one with the highest number of gas
because I have had direct experience of the issue in	my constituency	. A woman came over here as the wife of
. Let us take the feed-in tariff fiasco . In	my constituency	alone , we are losing many jobs , because a
What practical advice can the Secretary of State give to	my constituents	, as some 3,000 householders in my constituency face a
sport , that this is good enough for kids in	my constituency	?
a fair deal on jobs , getting young people in	my constituency	and others involved in working our way out of the
argument is best explained by reference to the case of	my constituent	, Neil Kenny , who raised his concerns about the
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 20: 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 Manchester is
again have a university . However , Nene college in	my constituency	hopes to change all that , and I support strongly
Enforcement Campaign-in Cardiff , and particularly to the work of	my constituent	, Professor John Shepherd , who works in the dental
and assets than non-disabled people . In London , where	my constituency	and the constituency of my hon . Friend the Member
in particular from the circumstances of students in Northampton .	My constituency	contains both a higher education and a further education college
the marine Bill on the grounds of its irrelevance to	my constituents	, because , like the hon . Lady , I
deepest concern for the families involved , especially given that	my constituency	neighbours that of my hon . Friend the Member for
services can expand on the slow line so that all	my constituents	benefit from the west coast main line upgrade ?
rehabilitation . \ n " , " The people of	my constituency	have been horrified by those cases , and it is
Labour Government we have achieved a tremendous amount . In	my constituency	the number of people claiming jobseeker's allowance has almost halved
they complain ? Where will the local accountability go ?	My constituents	very much value the highly accessible local service that they
n " , " Since helping the Jarrow marchers ,	my constituency	has continued to welcome people from throughout the UK ,
and not-for-profit groups , of which there are many in	my constituency	, doing immensely valuable work . They all too often
as soon as possible . Indeed , for some of	my constituents	, reform is already coming too late . \ n
bus travel in Wales . I have met pensioners in	my constituency	who say that it has transformed their lives . As
and Sir Malcolm Thornton . All have represented part of	my constituency	and all left this House on 20 April or 1
Ports is the operator at the port of Immingham in	my constituency	. The companies there firmly believe that they have paid
Conservative-controlled Bradford city council excluded the wonderful Ilkley lido in	my constituency	from the free swimming initiative for young people and pensioners
for my hon . Friend's reply , and many of	my constituents	who have come across the benefit integrity project will be
Tero was not properly treated and offer the apology that	my constituent	deserves . \ n "

Table 20: 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 , not only in	my constituency	but in many northern towns and cities , I see
on an issue that has been of great concern to	my constituents	. While I appreciate the cross-party consensus that exists on
In	my constituency	of West Lancashire , the national lottery has supported 266
to meet the skills gap in engineering and construction in	my constituency	. \ 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 consultation in	my constituency	on the pensioners tax credit was extremely successful . The
Government for investing in the city of Bradford , helping	my constituents	to realise their potential . But in reality little has
visited Dot To Dot , a community arts project in	my constituency	. It has a good record of involving the community
one regret the fact that Westminster , which covers half	my constituency	, has so far concentrated CCTV bids-I am sure with
also significant gaps in the Bill . One example from	my constituency	concerns a community hydro project in Saddleworth that might not
hon . Friend for that reply , but most of	my constituents	probably do not know what a low carbon transition plan
has provided opportunities where there were none before . In	my constituency	, there have been far more opportunities in the past
to find examples of such practices . Another case in	my constituency	, with which I am dealing , involves elderly victims
. \ n " , " The credit union in	my constituency	is fragile , because it serves an area in which
certainly applies to me because the acute trust that covers	my constituents	, who desperately need care , has the mother and
reveal a trend , and I see it happening in	my constituency	. It is a demonstrable fact that the polarisation between
	My constituent	, John Warren , has specifically asked me to raise
\ n " , " Bridges Project in Musselburgh in	my constituency	does a brilliant job in supporting young people . A
Spowart , a small firm of legal aid solicitors in	my constituency	. Solicitors at the firm are paid generally between £
, both as a national concern and as it affects	my constituency	. I am grateful to my hon . Friend for
, nor , sadly , are far too many of	my constituents	. \ 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 20: A random sample of KWIC's *(continued)*

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

Table 20: A random sample of KWIC's *(continued)*

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

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

Table 20: 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 campaign . But for now ,	my constituents	still face the prospect of seriously downgraded services at their
from and bugbear for my constituents . On behalf of	my constituents	and their families , I very much look forward to
" , " helped motorists and the hard-pressed hauliers in	my constituency-or	they could have looked at jobs for young people .
Staff at Trinity , Bluecoat and Fernwood schools in	my constituency	are desperate for extra investment in their buildings . Will
The point about geography is critical in Cumbria , where	my constituency	is . Under the proposals , we will end up
will affect disabled youngsters . The What ? centre in	my constituency	, which gives counselling to all youngsters , still does
closure of the offices is having a direct impact on	my constituency	. Walsall faces the closure of its HMRC office ,
. \ n " , " Frustration is evident among	my constituents	: for many years , they have felt marginalised and
, larger numbers of people are choosing to live in	my constituency	but work in London . If we are to take
ethnic minority children , of whom there are many in	my constituency	. \ n " , " We have dealt a
single parents in the country-I will return to that point-and	my constituents	think that the measure is unfair . How people in
should not come back from our holidays to find that	my constituents	, and those of my neighbours , have lost their
their area ; I fully intend to do so in	my constituency	. \ n " , " We also need better
too much movement . I want Airedale general hospital in	my constituency	not just to survive , but to prosper . It
" , " During the summer and autumn months ,	my constituents	and those of many other hon . Members were affected
put a human face on many of the difficulties that	my constituents	experience . \ n " , " In Newham ,
Parent Action Network , which has its national headquarters in	my constituency	. It has just received nearly £ 400,000 in lottery
sector . On Friday , an independent community pharmacist in	my constituency	told me that he estimated that the Government cuts would
it becomes an empty gesture . A community group in	my constituency	is setting up a community development trust , and it
since June and doubled since 2006 . Young people in	my constituency	have been particularly badly hit , with a 288 %
police get back to strength to defend the people in	my constituency	of Mitcham and Morden ?

Table 20: 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 massive economic opportunity for Wales and	my constituency	in particular . Will the Minister assure the House that
Nottingham that stands to lose most is the Meadows in	my constituency	. Before the last election , the Meadows , one
am here this afternoon specifically to represent the concerns of	my constituents	who are trade union members in Parliament , as they
. Nothing could be further from the truth , as	my constituency	exemplifies . As I have already said , I represent
making are the very ones that have been made by	my constituents	, by the constituents of my hon . Friends and-I
, but wanted to take the opportunity to read out	my constituent's	comments so that Ministers understand the worry and concern .
firm of Hickman and Rose , which is based in	my constituency	? She was due to speak at a conference organised
Majesty's Opposition . That public money could be used for	my constituent	Grace Ryder , aged 9 , who was recently diagnosed
changes that will affect 650 families and 1,500 children in	my constituency	. \ 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 20: A random sample of KWIC's *(continued)*

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

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