# 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 $\chi^2$ 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.

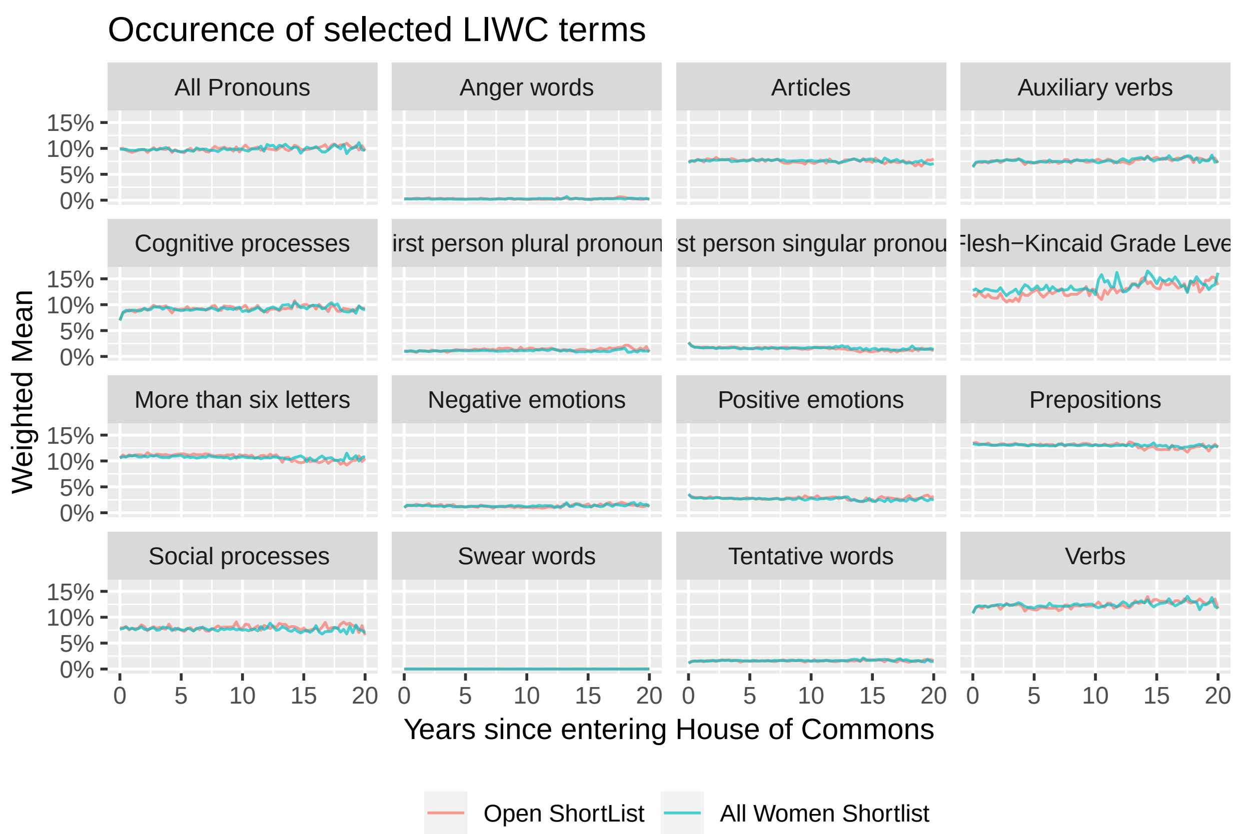


Figure 1: Occurence of selected LIWC terms

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.

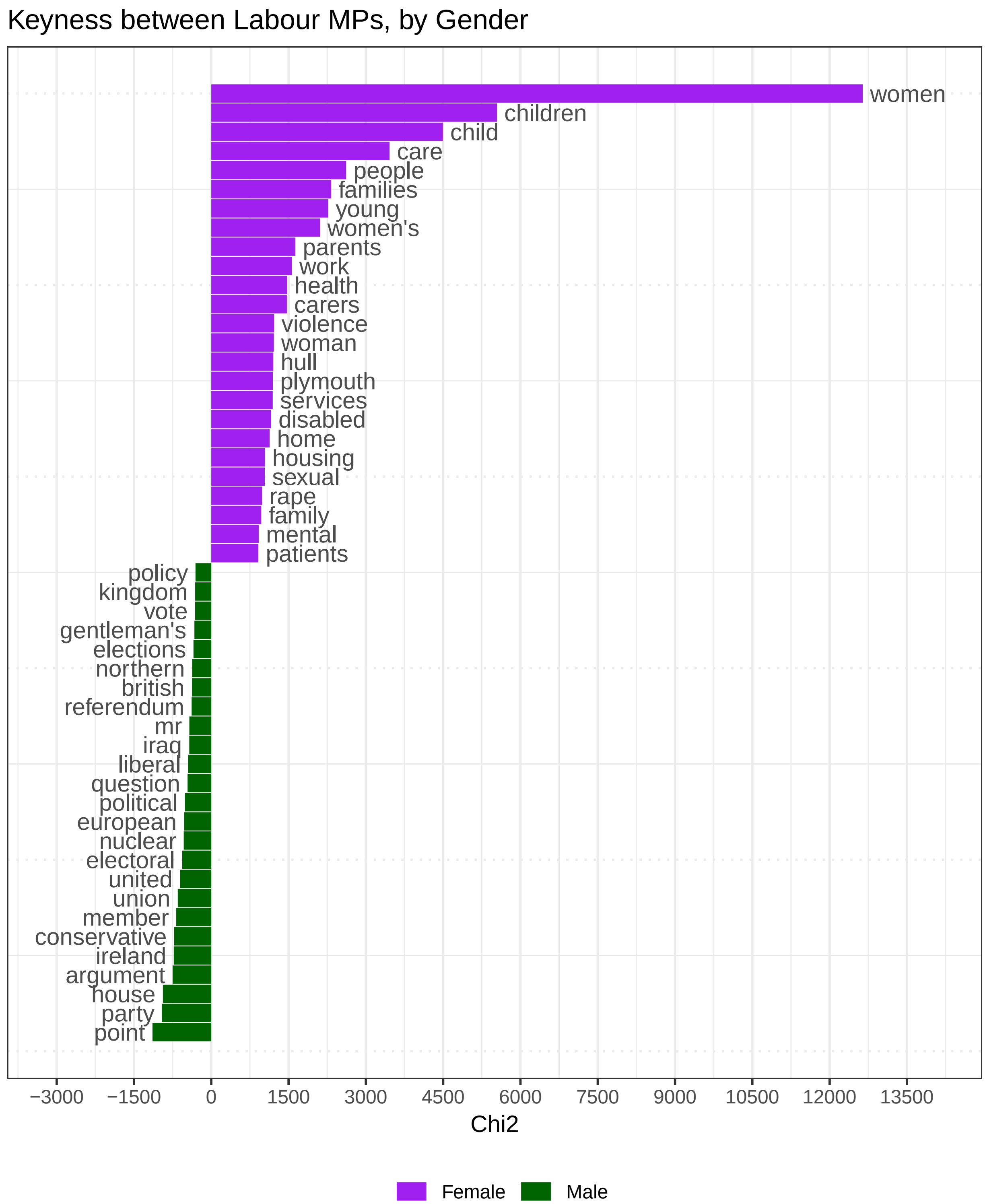


Figure 2: Keyness between Labour MPs, by Gender

#### 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.

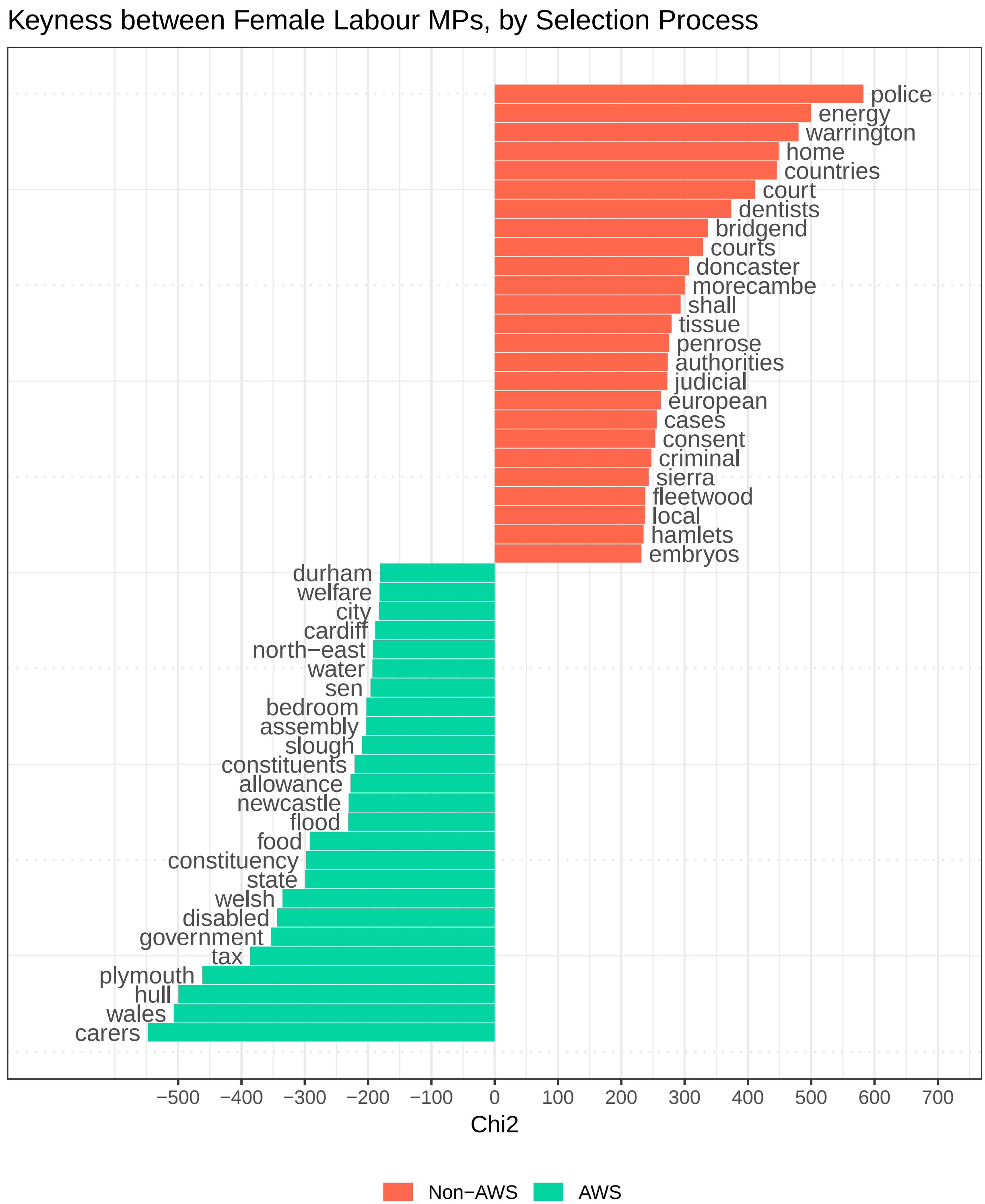


Figure 3: Keyness between Female Labour MPs, by Selection Process

### 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.

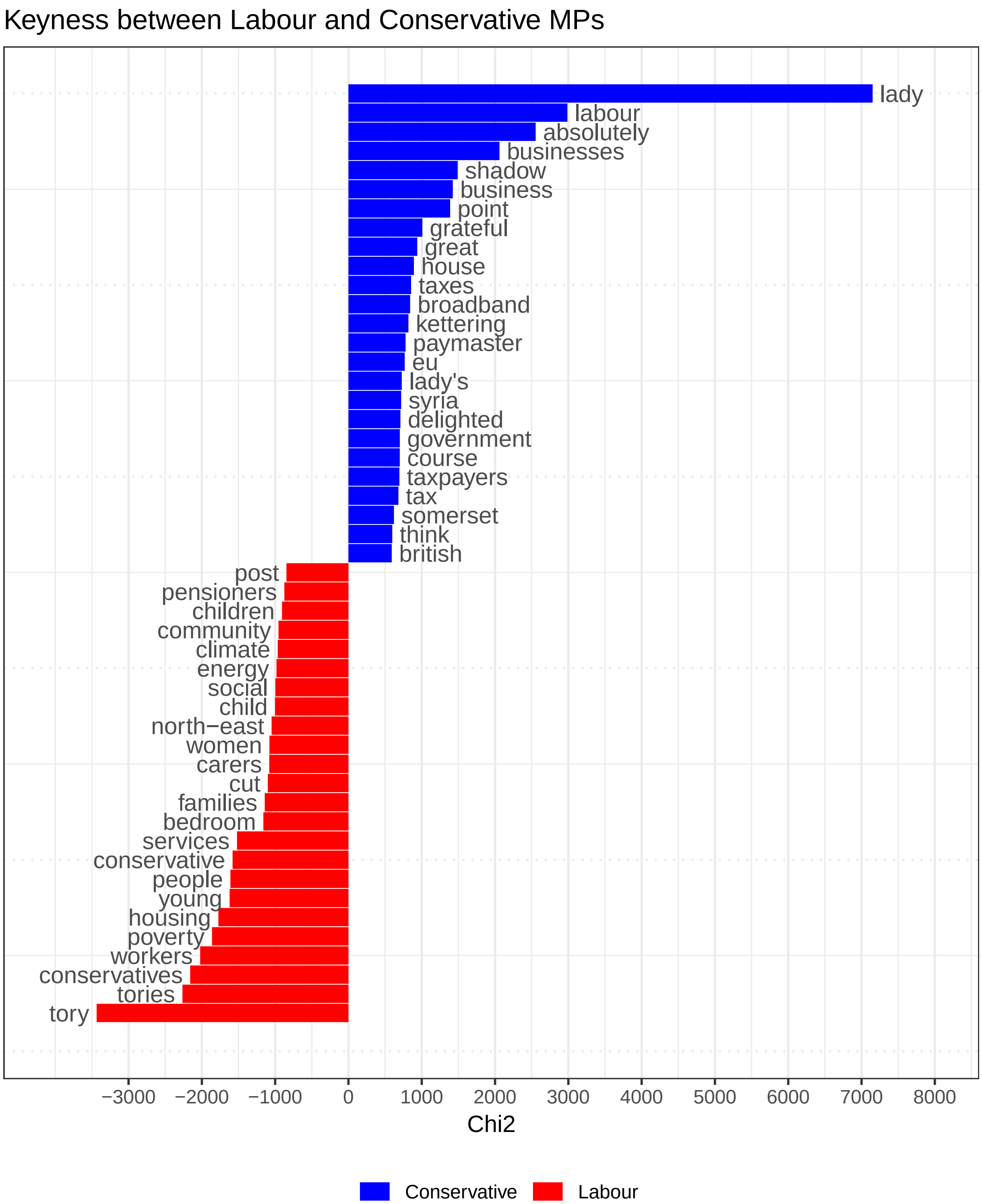


Figure 4: Keyness between Labour and Conservative MPs

## 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.

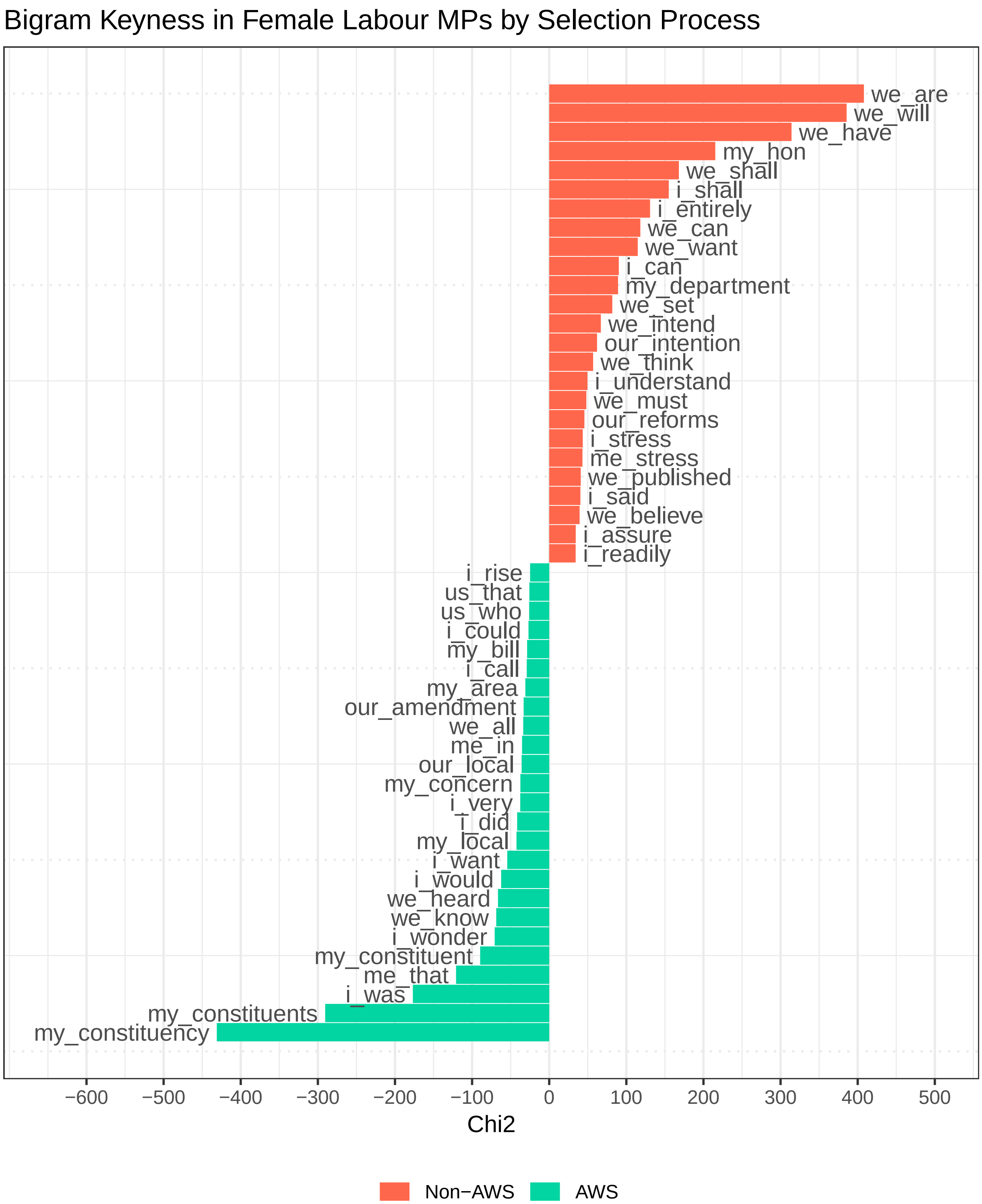


Figure 5: Bigram Keyness in Female Labour MPs by Selection Process

## 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 21, 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 12. 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

[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.

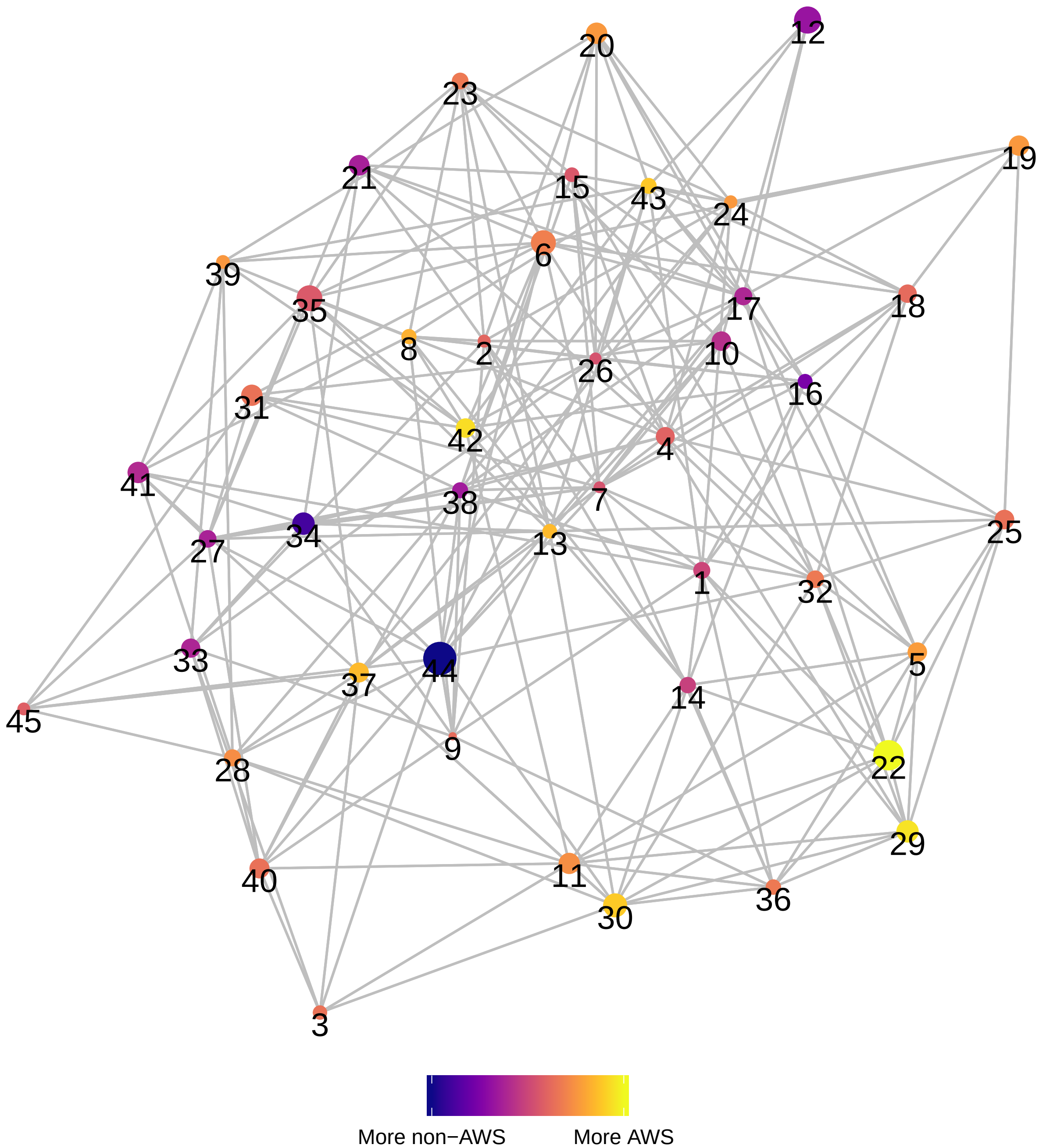


Figure 6: Fruchterman-Reingold plot of k45 Network

Table 9: Estimate Effects – k45

| Estimate | Standard Error | t value | P | Topic | Type | Stars |
|---|---|---|---|---|---|---|
| 0.0204951 | 0.0004357 | 47.0388656 | 0.0000000 | 1 | Intercept | *** |
| -0.0027715 | 0.0005642 | -4.9118480 | 0.0000009 | 1 | Shortlist | *** |
| 0.0111603 | 0.0003740 | 29.8431222 | 0.0000000 | 2 | Intercept | *** |
| 0.0000021 | 0.0004470 | 0.0046176 | 0.9963157 | 2 | Shortlist | |
| 0.0181549 | 0.0003848 | 47.1762985 | 0.0000000 | 3 | Intercept | *** |
| 0.0010537 | 0.0004747 | 2.2197525 | 0.0264383 | 3 | Shortlist | * |
| 0.0188190 | 0.0005151 | 36.5377744 | 0.0000000 | 4 | Intercept | *** |
| -0.0002286 | 0.0006446 | -0.3546268 | 0.7228701 | 4 | Shortlist | |
| 0.0155164 | 0.0005274 | 29.4196623 | 0.0000000 | 5 | Intercept | *** |
| 0.0041718 | 0.0006684 | 6.2416932 | 0.0000000 | 5 | Shortlist | *** |
| 0.0369191 | 0.0003572 | 103.3593472 | 0.0000000 | 6 | Intercept | *** |
| 0.0019932 | 0.0004520 | 4.4095241 | 0.0000104 | 6 | Shortlist | *** |
| 0.0193233 | 0.0002769 | 69.7757473 | 0.0000000 | 7 | Intercept | *** |
| -0.0015222 | 0.0003369 | -4.5181702 | 0.0000062 | 7 | Shortlist | *** |
| 0.0088852 | 0.0003911 | 22.7208888 | 0.0000000 | 8 | Intercept | *** |
| 0.0056158 | 0.0005583 | 10.0591596 | 0.0000000 | 8 | Shortlist | *** |
| 0.0098254 | 0.0003698 | 26.5672671 | 0.0000000 | 9 | Intercept | *** |
| 0.0004830 | 0.0004499 | 1.0736694 | 0.2829740 | 9 | Shortlist | |
| 0.0216374 | 0.0005614 | 38.5414647 | 0.0000000 | 10 | Intercept | *** |
| -0.0047448 | 0.0006901 | -6.8754406 | 0.0000000 | 10 | Shortlist | *** |
| 0.0315911 | 0.0004328 | 72.9868880 | 0.0000000 | 11 | Intercept | *** |
| 0.0032136 | 0.0005360 | 5.9955681 | 0.0000000 | 11 | Shortlist | *** |
| 0.0346276 | 0.0007013 | 49.3765546 | 0.0000000 | 12 | Intercept | *** |
| -0.0072062 | 0.0009216 | -7.8193054 | 0.0000000 | 12 | Shortlist | *** |
| 0.0116992 | 0.0003687 | 31.7292056 | 0.0000000 | 13 | Intercept | *** |
| 0.0062273 | 0.0005079 | 12.2613344 | 0.0000000 | 13 | Shortlist | *** |
| 0.0170285 | 0.0004634 | 36.7487676 | 0.0000000 | 14 | Intercept | *** |
| -0.0032567 | 0.0006142 | -5.3027038 | 0.0000001 | 14 | Shortlist | *** |
| 0.0166912 | 0.0003689 | 45.2502390 | 0.0000000 | 15 | Intercept | *** |
| -0.0011792 | 0.0004466 | -2.6404137 | 0.0082821 | 15 | Shortlist | ** |
| 0.0254973 | 0.0004412 | 57.7934363 | 0.0000000 | 16 | Intercept | *** |
| -0.0092979 | 0.0005123 | -18.1499708 | 0.0000000 | 16 | Shortlist | *** |
| 0.0259225 | 0.0004042 | 64.1249473 | 0.0000000 | 17 | Intercept | *** |
| -0.0055092 | 0.0005029 | -10.9538546 | 0.0000000 | 17 | Shortlist | *** |
| 0.0177248 | 0.0004528 | 39.1456454 | 0.0000000 | 18 | Intercept | *** |
| 0.0004121 | 0.0005445 | 0.7568560 | 0.4491383 | 18 | Shortlist | |
| 0.0165421 | 0.0005372 | 30.7921455 | 0.0000000 | 19 | Intercept | *** |
| 0.0039280 | 0.0006518 | 6.0267450 | 0.0000000 | 19 | Shortlist | *** |
| 0.0181318 | 0.0005770 | 31.4254794 | 0.0000000 | 20 | Intercept | *** |
| 0.0038897 | 0.0006771 | 5.7446879 | 0.0000000 | 20 | Shortlist | *** |
| 0.0240590 | 0.0006107 | 39.3976962 | 0.0000000 | 21 | Intercept | *** |
| -0.0061956 | 0.0007251 | -8.5444161 | 0.0000000 | 21 | Shortlist | *** |
| 0.0361958 | 0.0006524 | 55.4817458 | 0.0000000 | 22 | Intercept | *** |
| 0.0100003 | 0.0008491 | 11.7771875 | 0.0000000 | 22 | Shortlist | *** |
| 0.0131313 | 0.0005736 | 22.8924484 | 0.0000000 | 23 | Intercept | *** |

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

| Estimate | Standard Error | t value | P | Topic | Type | Stars |
|---|---|---|---|---|---|---|
| 0.0015186 | 0.0006502 | 2.3357162 | 0.0195084 | 23 | Shortlist | * |
| 0.0082622 | 0.0003690 | 22.3906594 | 0.0000000 | 24 | Intercept | *** |
| 0.0039135 | 0.0004591 | 8.5248900 | 0.0000000 | 24 | Shortlist | *** |
| 0.0201256 | 0.0004772 | 42.1772030 | 0.0000000 | 25 | Intercept | *** |
| 0.0008824 | 0.0005734 | 1.5388927 | 0.1238344 | 25 | Shortlist | |
| 0.0117383 | 0.0003692 | 31.7957233 | 0.0000000 | 26 | Intercept | *** |
| -0.0017104 | 0.0004553 | -3.7563020 | 0.0001726 | 26 | Shortlist | *** |
| 0.0214066 | 0.0004909 | 43.6080908 | 0.0000000 | 27 | Intercept | *** |
| -0.0059868 | 0.0005908 | -10.1331915 | 0.0000000 | 27 | Shortlist | *** |
| 0.0143883 | 0.0004594 | 31.3221513 | 0.0000000 | 28 | Intercept | *** |
| 0.0031430 | 0.0005676 | 5.5377105 | 0.0000000 | 28 | Shortlist | *** |
| 0.0198918 | 0.0005707 | 34.8529943 | 0.0000000 | 29 | Intercept | *** |
| 0.0087491 | 0.0007096 | 12.3302419 | 0.0000000 | 29 | Shortlist | *** |
| 0.0396870 | 0.0003927 | 101.0746740 | 0.0000000 | 30 | Intercept | *** |
| 0.0072088 | 0.0004836 | 14.9080255 | 0.0000000 | 30 | Shortlist | *** |
| 0.0327820 | 0.0004285 | 76.5078922 | 0.0000000 | 31 | Intercept | *** |
| 0.0010358 | 0.0005401 | 1.9177144 | 0.0551507 | 31 | Shortlist | |
| 0.0267140 | 0.0003235 | 82.5682752 | 0.0000000 | 32 | Intercept | *** |
| 0.0015700 | 0.0004071 | 3.8566176 | 0.0001151 | 32 | Shortlist | *** |
| 0.0272253 | 0.0005598 | 48.6337038 | 0.0000000 | 33 | Intercept | *** |
| -0.0056761 | 0.0006441 | -8.8130920 | 0.0000000 | 33 | Shortlist | *** |
| 0.0323227 | 0.0005824 | 55.4985666 | 0.0000000 | 34 | Intercept | *** |
| -0.0127358 | 0.0007145 | -17.8254003 | 0.0000000 | 34 | Shortlist | *** |
| 0.0283326 | 0.0006990 | 40.5305987 | 0.0000000 | 35 | Intercept | *** |
| -0.0010465 | 0.0008688 | -1.2045914 | 0.2283646 | 35 | Shortlist | |
| 0.0157183 | 0.0003785 | 41.5295616 | 0.0000000 | 36 | Intercept | *** |
| 0.0015106 | 0.0004918 | 3.0716326 | 0.0021296 | 36 | Shortlist | ** |
| 0.0236898 | 0.0003723 | 63.6244645 | 0.0000000 | 37 | Intercept | *** |
| 0.0061934 | 0.0004939 | 12.5408451 | 0.0000000 | 37 | Shortlist | *** |
| 0.0280932 | 0.0003783 | 74.2669410 | 0.0000000 | 38 | Intercept | *** |
| -0.0065536 | 0.0005128 | -12.7808644 | 0.0000000 | 38 | Shortlist | *** |
| 0.0109064 | 0.0003871 | 28.1746087 | 0.0000000 | 39 | Intercept | *** |
| 0.0038214 | 0.0004934 | 7.7454016 | 0.0000000 | 39 | Shortlist | *** |
| 0.0285239 | 0.0004084 | 69.8489231 | 0.0000000 | 40 | Intercept | *** |
| 0.0009309 | 0.0004652 | 2.0011298 | 0.0453817 | 40 | Shortlist | * |
| 0.0259846 | 0.0005548 | 46.8332442 | 0.0000000 | 41 | Intercept | *** |
| -0.0052635 | 0.0006605 | -7.9686725 | 0.0000000 | 41 | Shortlist | *** |
| 0.0168733 | 0.0004266 | 39.5551893 | 0.0000000 | 42 | Intercept | *** |
| 0.0083566 | 0.0005743 | 14.5508370 | 0.0000000 | 42 | Shortlist | *** |
| 0.0132703 | 0.0003983 | 33.3144736 | 0.0000000 | 43 | Intercept | *** |
| 0.0070761 | 0.0005366 | 13.1880997 | 0.0000000 | 43 | Shortlist | *** |
| 0.0676878 | 0.0004210 | 160.7921664 | 0.0000000 | 44 | Intercept | *** |
| -0.0154158 | 0.0005242 | -29.4053779 | 0.0000000 | 44 | Shortlist | *** |
| 0.0168136 | 0.0003105 | 54.1483487 | 0.0000000 | 45 | Intercept | *** |
| -0.0005819 | 0.0003854 | -1.5096692 | 0.1311317 | 45 | Shortlist | |

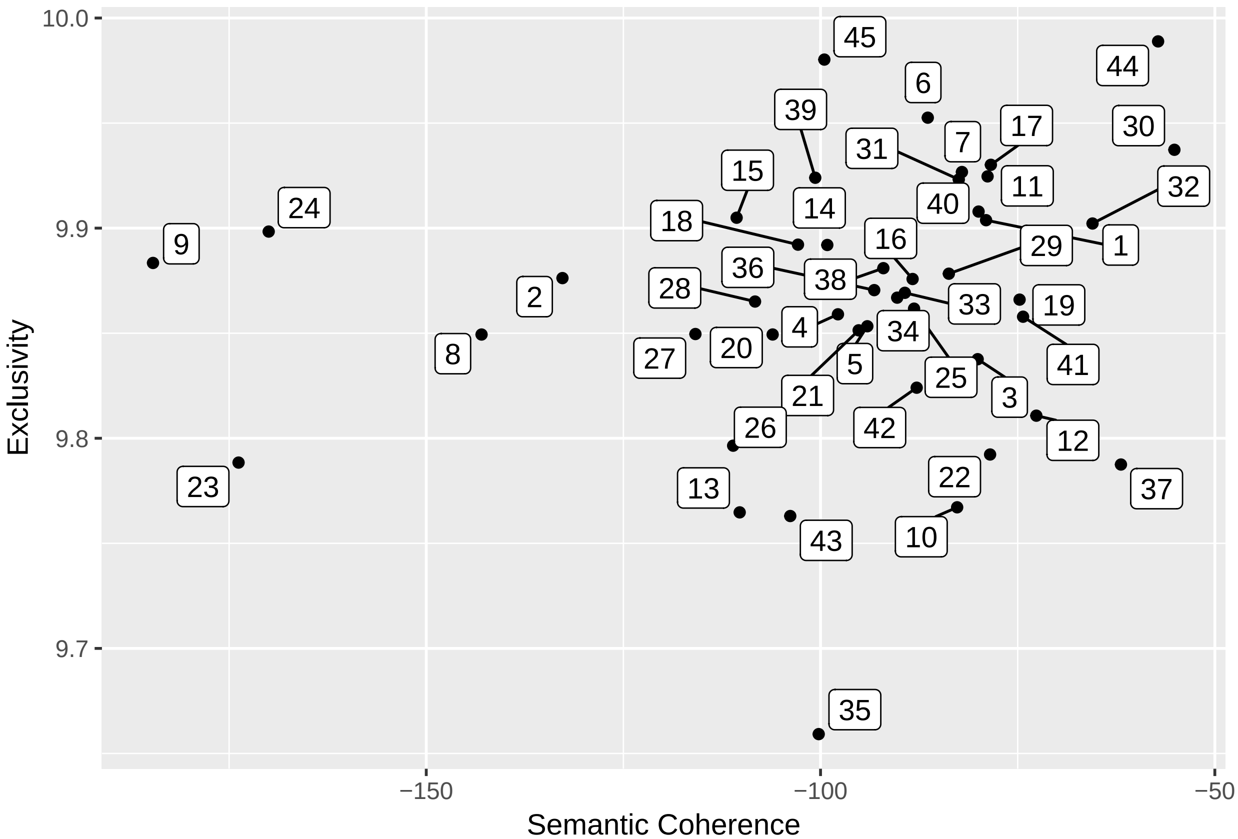


Figure 7: Coherence of k45 Topic Models

Table 10: Distribution of Topics Among Female Labour MPs – k45

| Topic | One or more speeches | Five or more speeches |
|---|---|---|
| Business | 140 | 72 |
| Disease | 143 | 74 |
| Parties | 152 | 96 |
| Health Care | 155 | 114 |
| Disasters | 150 | 79 |
| Energy | 128 | 57 |
| Volunteering | 132 | 64 |
| Infrastructure | 132 | 57 |
| Local authorities | 141 | 72 |
| Universities and Skills | 149 | 87 |
| Schools | 139 | 96 |
| Roads | 128 | 55 |
| Transport | 149 | 89 |
| Police | 147 | 81 |
| Budgets and tax | 157 | 127 |
| Drugs | 125 | 66 |
| Culture and sport | 131 | 66 |
| Children and familie | 143 | 82 |
| Planning and land-use | 113 | 45 |

Table 10: Distribution of Topics Among Female Labour MPs – k45
*(continued)*

| Topic | One or more speeches | Five or more speeches |
|---|---|---|
| Security | 127 | 61 |
| Elections | 135 | 70 |
| Benefits and pensions | 151 | 93 |
| Members | 129 | 67 |
| Call to action | 156 | 116 |
| Reports | 155 | 101 |
| Disability | 144 | 86 |
| Amendments | 123 | 57 |
| Justice | 146 | 82 |
| Military intervention | 155 | 112 |
| Financial system | 124 | 56 |
| Debate | 161 | 105 |
| Public bodies | 119 | 52 |
| Devolution | 104 | 43 |
| Gender | 149 | 85 |
| Bills | 136 | 79 |
| European Union | 152 | 91 |
| Environment | 143 | 89 |
| Constituency | 151 | 81 |
| Responses | 158 | 123 |
| Interventions | 120 | 40 |
| Housing | 141 | 74 |
| Questions | 165 | 132 |
| Technology | 121 | 49 |
| Food and farming | 123 | 57 |
| Animals | 109 | 32 |

Table 11: Count and Distribution of Topics – k45

| Topic Number | AWS Speeches | Percent of AWS Speeches | Non-AWS Speeches | Percent of non-AWS Speeches | Male MP Speeches | Percent of Male MP Speeches |
|---|---|---|---|---|---|---|
| Topic 1 | 759 | 1.41% | 576 | 2.07% | 2,841 | 1.68% |
| Topic 2 | 552 | 1.03% | 297 | 1.07% | 1,908 | 1.13% |
| Topic 3 | 667 | 1.24% | 323 | 1.16% | 2,646 | 1.56% |
| Topic 4 | 1,092 | 2.03% | 568 | 2.04% | 588 | 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% |

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

| Topic Number | AWS Speeches | Percent of AWS Speeches | Non-AWS Speeches | Percent of non-AWS Speeches | Male MP Speeches | Percent of Male MP Speeches |
|---|---|---|---|---|---|---|
| Topic 14 | 673 | 1.25% | 569 | 2.04% | 2,183 | 1.29% |
| Topic 15 | 668 | 1.24% | 351 | 1.26% | 1,279 | 0.76% |
| Topic 16 | 477 | 0.89% | 569 | 2.04% | 2,165 | 1.28% |
| Topic 17 | 855 | 1.59% | 649 | 2.33% | 3,107 | 1.83% |
| Topic 18 | 1,058 | 1.97% | 512 | 1.84% | 3,239 | 1.91% |
| Topic 19 | 1,430 | 2.66% | 529 | 1.9% | 3,491 | 2.06% |
| Topic 20 | 1,601 | 2.98% | 582 | 2.09% | 4,181 | 2.47% |
| Topic 21 | 1,199 | 2.23% | 815 | 2.93% | 3,112 | 1.84% |
| Topic 22 | 3,712 | 6.9% | 1,295 | 4.65% | 10,692 | 6.31% |
| Topic 23 | 903 | 1.68% | 386 | 1.39% | 1,762 | 1.04% |
| Topic 24 | 647 | 1.2% | 219 | 0.79% | 1,773 | 1.05% |
| Topic 25 | 1,179 | 2.19% | 619 | 2.22% | 1,275 | 0.75% |
| Topic 26 | 486 | 0.9% | 291 | 1.04% | 1,363 | 0.8% |
| Topic 27 | 766 | 1.42% | 652 | 2.34% | 2,041 | 1.21% |
| Topic 28 | 1,006 | 1.87% | 328 | 1.18% | 4,391 | 2.59% |
| Topic 29 | 1,818 | 3.38% | 594 | 2.13% | 3,335 | 1.97% |
| Topic 30 | 2,247 | 4.18% | 621 | 2.23% | 8,740 | 5.16% |
| Topic 31 | 1,482 | 2.76% | 683 | 2.45% | 4,975 | 2.94% |
| Topic 32 | 992 | 1.84% | 429 | 1.54% | 1,624 | 0.96% |
| Topic 33 | 971 | 1.81% | 742 | 2.66% | 4,525 | 2.67% |
| Topic 34 | 1,215 | 2.26% | 1,239 | 4.45% | 4,450 | 2.63% |
| Topic 35 | 2,153 | 4% | 1,223 | 4.39% | 9,983 | 5.9% |
| Topic 36 | 755 | 1.4% | 360 | 1.29% | 2,030 | 1.2% |
| Topic 37 | 1,409 | 2.62% | 460 | 1.65% | 5,138 | 3.03% |
| Topic 38 | 676 | 1.26% | 508 | 1.82% | 2,387 | 1.41% |
| Topic 39 | 716 | 1.33% | 203 | 0.73% | 2,374 | 1.4% |
| Topic 40 | 1,344 | 2.5% | 539 | 1.93% | 5,389 | 3.18% |
| Topic 41 | 1,271 | 2.36% | 918 | 3.29% | 5,573 | 3.29% |
| Topic 42 | 1,380 | 2.57% | 394 | 1.41% | 3,854 | 2.28% |
| Topic 43 | 896 | 1.67% | 277 | 0.99% | 1,823 | 1.08% |
| Topic 44 | 3,309 | 6.15% | 2,931 | 10.52% | 19,842 | 11.72% |
| Topic 45 | 521 | 0.97% | 320 | 1.15% | 2,417 | 1.43% |

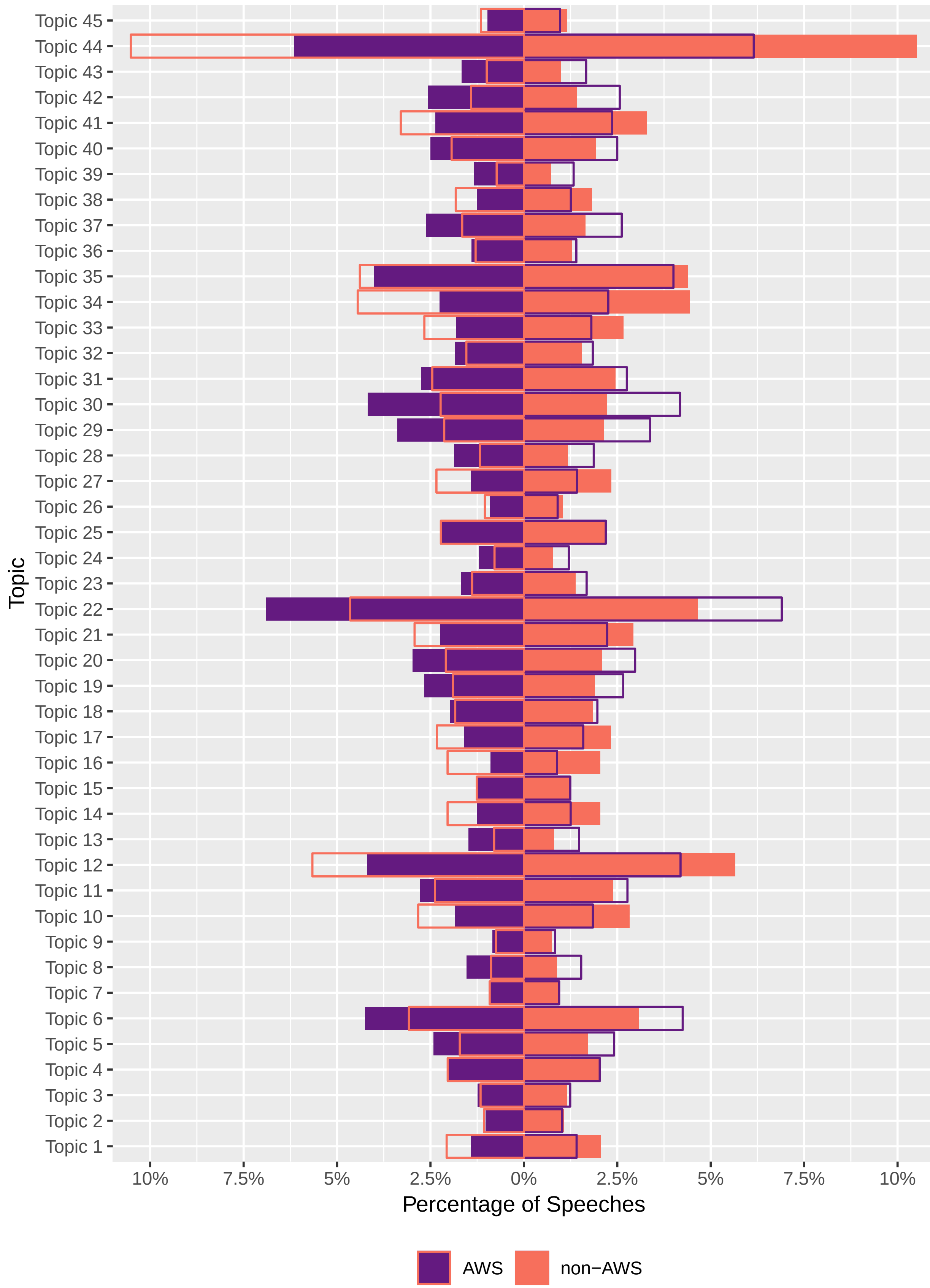


Figure 8: k45 Pyramid Chart

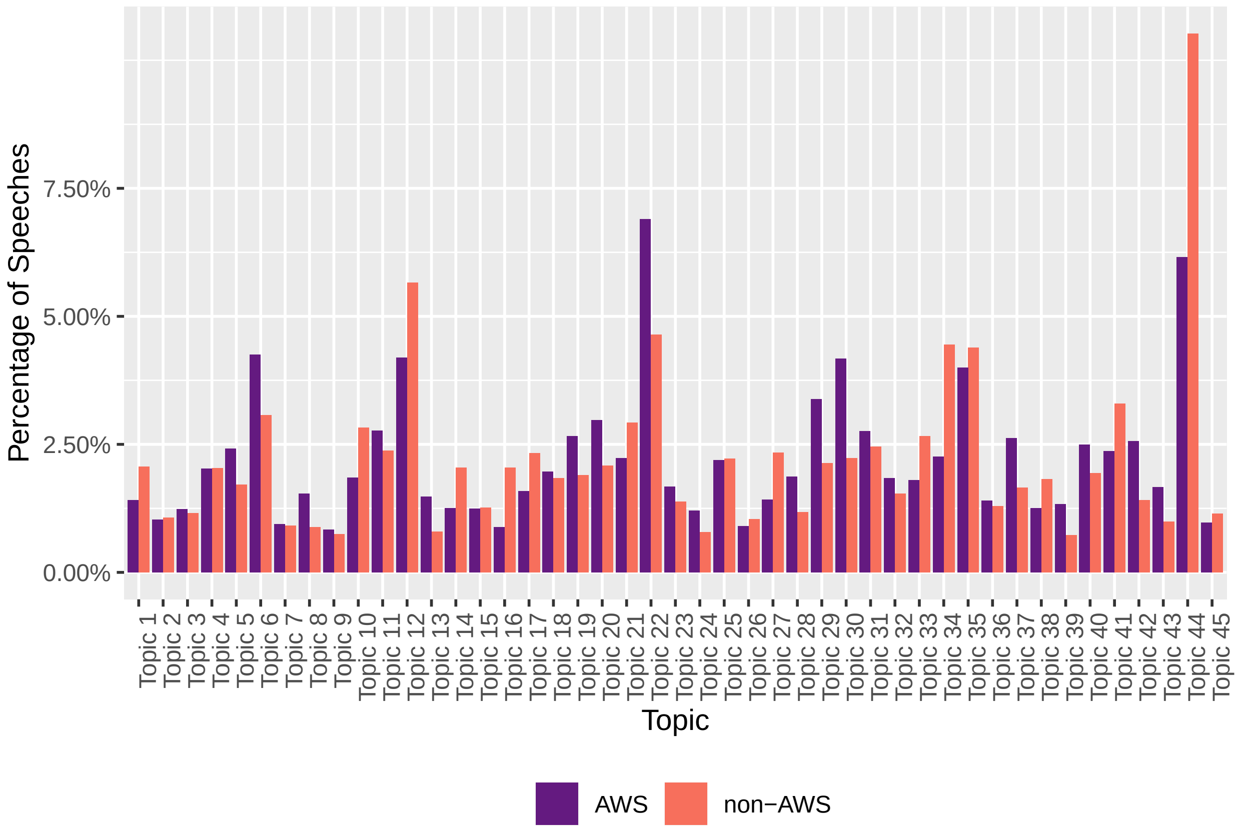


Figure 9: k45 Bar Chart

#### 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 - k45

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

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

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

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

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

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

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

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

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

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

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

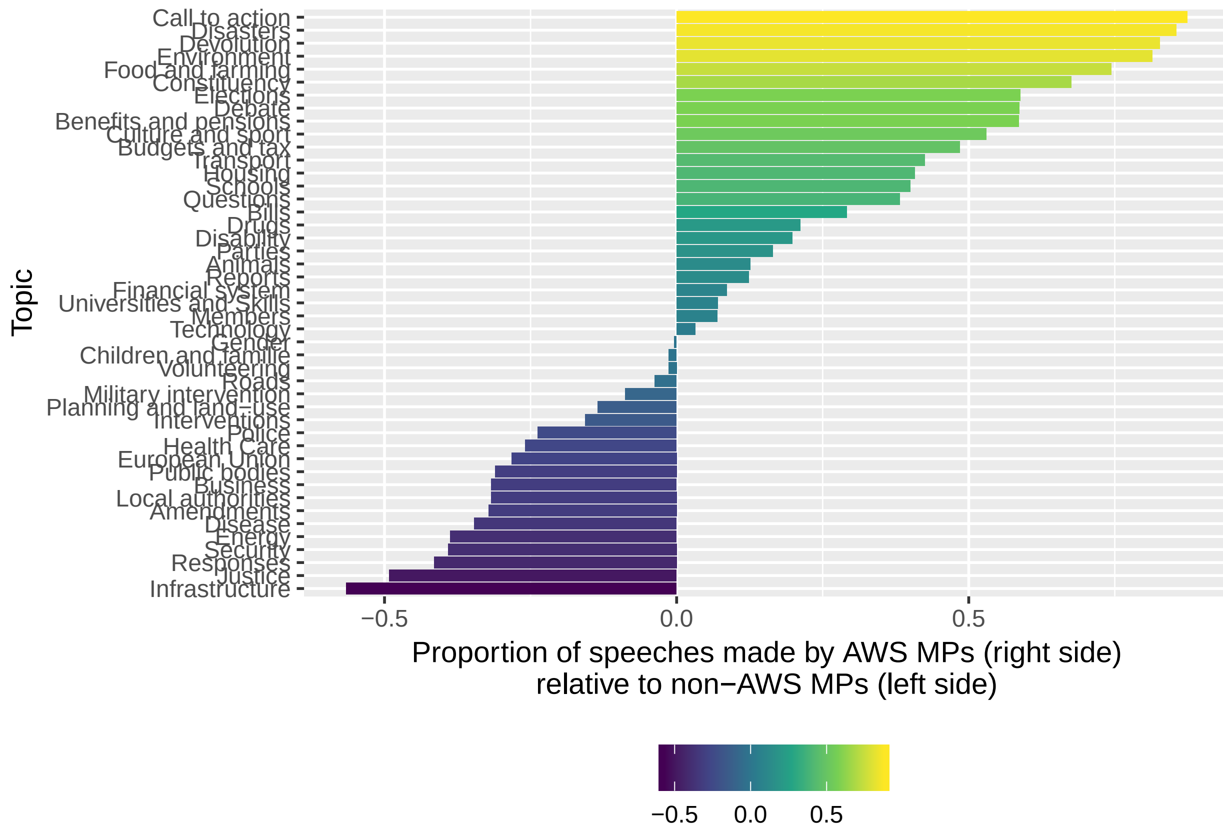


Figure 10: k45 Topic Proportions

### 2.6.2 Full topic model summary - k45

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

```
## Topic 1 Top Words:
##       Highest Prob: business, businesses, companies, small, tax, company, sector
##       FREX: businesses, medium-sized, avoidance, employees, enterprise, corporation, business
##       Lift: 1,643, 3.12, 32.2, aaronson, anti-abuse, anti-tax, bacs
##       Score: businesses, tax, companies, business, company, avoidance, hmrc
## Topic 2 Top Words:
##       Highest Prob: safety, road, bbc, air, licence, car, vehicles
##       FREX: caa, herbal, vehicles, primodos, accidents, taxi, bbc
##       Lift: aerodromes, blagdon, bonfires, caa, csm, gatwick's, grantee
##       Score: bbc, safety, vehicles, traffic, licence, road, fireworks
## Topic 3 Top Words:
##       Highest Prob: member, members, debate, said, made, also, north
##       FREX: member, thoughtful, spoke, eastmr, westmr, hayes, eloquently
##       Lift: acoba, erdington, islesmr, northsteve, sedgemore, shoreditchmr, strathspey
##       Score: member, north, members, spoke, east, south, debate
## Topic 4 Top Words:
##       Highest Prob: women, violence, men, domestic, equality, women's, pay
##       FREX: gender, women, women's, fgm, discrimination, equality, female
##       Lift: 77p, amirah, berelowitz, bishoprics, board-level, bride, brothel-keeping
##       Score: women, violence, women's, men, equality, sexual, discrimination
## Topic 5 Top Words:
```

```
##       Highest Prob: housing, homes, private, social, home, affordable, london
##       FREX: rent, tenants, landlords, rented, homelessness, homeless, rents
##       Lift: 1,624, afon, bramwell, bron, clearsprings, commonhold, infestation
##       Score: housing, homes, rent, tenants, rented, landlords, affordable
## Topic 6 Top Words:
##       Highest Prob: agree, ensure, made, support, make, aware, welcome
##       FREX: agree, aware, progress, steps, thank, friend's, assessment
##       Lift: ina, manya, ona, 10.42, 101269, 101548, 101549
##       Score: statement, agree, department, assessment, aware, steps, progress
## Topic 7 Top Words:
##       Highest Prob: information, service, access, advice, available, services, staff
##       FREX: information, data, advice, pilot, broadband, digital, communication
##       Lift: north-westdr, saneline, 1,001, 1,752, 1,997, 109648, 114061
##       Score: information, service, advice, data, access, staff, digital
## Topic 8 Top Words:
##       Highest Prob: food, plymouth, farmers, industry, environment, waste, rural
##       FREX: marine, fishing, fisheries, fishermen, cod, beef, gm
##       Lift: fishermen, incineration, inshore, mmo, 0157, 1-tonne, 1,004
##       Score: food, farmers, plymouth, marine, fishing, fisheries, fishermen
## Topic 9 Top Words:
##       Highest Prob: regulation, insurance, regulatory, animals, code, industry, fsa
##       FREX: dogs, dog, policyholders, fur, mink, sia, mesothelioma
##       Lift: 13652, 13653, 13654, arculus, attachment-free, attribution, bee-friendly
##       Score: fsa, animals, regulation, dogs, regulatory, insurance, animal
## Topic 10 Top Words:
##       Highest Prob: health, treatment, cancer, mental, research, medical, disease
##       FREX: embryos, prostate, cervical, hepatitis, cancers, transplant, fertilisation
##       Lift: embryonic, endometriosis, fibrosis, hfea, piercing, @cfaware, #500
##       Score: cancer, mental, health, patients, disease, treatment, screening
## Topic 11 Top Words:
##       Highest Prob: government, labour, conservative, policy, opposition, party, government's
##       FREX: conservative, conservatives, liberal, tory, tories, democrats, labour
##       Lift: lib, #nationalistsconfused, 1.135, 1125, 15-years, 1945-51, 1980s-interruption
##       Score: conservative, government, labour, party, liberal, opposition, conservatives
## Topic 12 Top Words:
##       Highest Prob: health, care, nhs, services, hospital, patients, service
##       FREX: dentists, dentistry, helier, dental, pct, dentist, nurses
##       Lift: #10.89, #14, #20, #225, #3.3, #47, #620
##       Score: nhs, patients, care, hospital, health, patient, hospitals
## Topic 13 Top Words:
##       Highest Prob: family, constituent, mr, families, man, years, fire
##       FREX: firefighters, mrs, constituent, fire, died, son, daughter
##       Lift: firefighters, #ftvote, #timeforthetruth, 03, 0315, 0345, 1,000-year
##       Score: constituent, fire, mr, mrs, died, family, ambulance
## Topic 14 Top Words:
##       Highest Prob: energy, market, fuel, companies, water, prices, price
##       FREX: ofgem, fuel, electricity, gas, supplier, energy, tariff
##       Lift: 1,105, 1,345, 106.89, 6,196, 840,000, abebrese, able-to-pay
##       Score: energy, fuel, prices, consumers, gas, water, electricity
## Topic 15 Top Words:
##       Highest Prob: community, organisations, groups, voluntary, communities, society, sector
##       FREX: volunteering, voluntary, charities, prisons, organisations, church, volunteers
##       Lift: aid-style, allison's, atheists, bronzefield, caron, cascs, catholicism
##       Score: community, prison, organisations, voluntary, charities, prisons, prisoners
```

```
## Topic 16 Top Words:
##       Highest Prob: new, investment, areas, post, office, building, rural
##       FREX: post, offices, mail, regeneration, investment, rural, urban
##       Lift: sub-post, #1.8, #21.5, #210, #28.5, #450, 0207
##       Score: investment, post, rural, regeneration, offices, mail, infrastructure
## Topic 17 Top Words:
##       Highest Prob: local, authorities, funding, council, authority, areas, government
##       FREX: authorities, local, councils, funding, authority, grant, formula
##       Lift: banham, brs-bids, central-local, devolves, lga's, maas, merrick
##       Score: local, authorities, funding, councils, authority, council, county
## Topic 18 Top Words:
##       Highest Prob: education, skills, training, young, students, university, college
##       FREX: students, apprenticeships, universities, ema, fe, graduates, colleges
##       Lift: 16-19, 16-to-19, apostrophe, apprenticeships, as-levels, baccalaureate, co-financed
##       Score: students, education, skills, training, young, apprenticeships, universities
## Topic 19 Top Words:
##       Highest Prob: schools, school, education, children, teachers, parents, pupils
##       FREX: schools, teachers, pupils, sen, academies, ofsted, pupil
##       Lift: 11-plus, 26-place, academisation, academised, asperger, authority-maintained, 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
```

#### 2.6.3 Full topic model estimate summary - k45

```
##
## Call:
## estimateEffect(formula = 1:45 ~ short_list, stmobj = topic_model_k45,
##     metadata = lab_corpus_fem_stm$meta, uncertainty = "Global")
##
##
## Topic 1:
##
```

```
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0204943  0.0004326  47.369 < 0.0000000000000002 ***
## short_listTRUE -0.0027730  0.0005614  -4.939          0.000000786 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 2:
##
## Coefficients:
##                   Estimate  Std. Error t value            Pr(>|t|)
## (Intercept)    0.011157346 0.000376890  29.604 <0.0000000000000002 ***
## short_listTRUE 0.000007184 0.000446309   0.016               0.987
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0181553  0.0003824  47.475 <0.0000000000000002 ***
## short_listTRUE 0.0010534  0.0004736   2.224              0.0261 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0188182  0.0005082  37.028 <0.0000000000000002 ***
## short_listTRUE -0.0002344  0.0006456  -0.363               0.717
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 5:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0155088  0.0005330  29.100 < 0.0000000000000002 ***
## short_listTRUE 0.0041825  0.0006762   6.185       0.000000000623 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 6:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0369215  0.0003579 103.167 < 0.0000000000000002 ***
## short_listTRUE 0.0019861  0.0004522   4.392            0.0000113 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0193253  0.0002825  68.397 < 0.0000000000000002 ***
## short_listTRUE -0.0015241  0.0003423  -4.452           0.00000851 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 8:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0088805  0.0003904   22.75 <0.0000000000000002 ***
## short_listTRUE 0.0056217  0.0005610   10.02 <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)    0.0098214  0.0003641  26.974 <0.0000000000000002 ***
## short_listTRUE 0.0004890  0.0004463   1.096               0.273
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0216379  0.0005611  38.560 < 0.0000000000000002 ***
## short_listTRUE -0.0047485  0.0006934  -6.848     0.00000000000754 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0315972  0.0004334  72.912 < 0.0000000000000002 ***
## short_listTRUE 0.0032074  0.0005345   6.001        0.00000000197 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
```

```
## Topic 12:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0346226  0.0006922  50.019 < 0.0000000000000002 ***
## short_listTRUE -0.0072002  0.0009113  -7.901  0.00000000000000281 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0117016  0.0003674   31.85 <0.0000000000000002 ***
## short_listTRUE 0.0062224  0.0005053   12.31 <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)     0.0170251  0.0004576  37.204 < 0.0000000000000002 ***
## short_listTRUE -0.0032528  0.0006131  -5.306          0.000000112 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0166963  0.0003708  45.024 < 0.0000000000000002 ***
## short_listTRUE -0.0011872  0.0004433  -2.678              0.00741 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 16:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0254984  0.0004315   59.09 <0.0000000000000002 ***
## short_listTRUE -0.0093026  0.0005046  -18.44 <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)     0.0259203  0.0004098   63.26 <0.0000000000000002 ***
## short_listTRUE -0.0055061  0.0005067  -10.87 <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)    0.0177227  0.0004477  39.590 <0.0000000000000002 ***
## short_listTRUE 0.0004174  0.0005417   0.771               0.441
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 19:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0165327  0.0005390  30.676 < 0.0000000000000002 ***
## short_listTRUE 0.0039444  0.0006547   6.025         0.0000000017 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0181321  0.0005756  31.501 < 0.0000000000000002 ***
## short_listTRUE 0.0038848  0.0006787   5.724         0.0000000105 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0240492  0.0006114  39.332 <0.0000000000000002 ***
## short_listTRUE -0.0061885  0.0007254  -8.531 <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)    0.0361998  0.0006453   56.10 <0.0000000000000002 ***
## short_listTRUE 0.0099927  0.0008391   11.91 <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)    0.0131298  0.0005697  23.046 <0.0000000000000002 ***
## short_listTRUE 0.0015181  0.0006380   2.379              0.0173 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0082637  0.0003729  22.162 <0.0000000000000002 ***
## short_listTRUE 0.0039102  0.0004573   8.551 <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)    0.0201195  0.0004655  43.220 <0.0000000000000002 ***
## short_listTRUE 0.0008854  0.0005699   1.554                0.12
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0117437  0.0003739  31.411 < 0.0000000000000002 ***
## short_listTRUE -0.0017147  0.0004590  -3.735             0.000188 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0214094  0.0004909  43.613 <0.0000000000000002 ***
## short_listTRUE -0.0059906  0.0005997  -9.989 <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)    0.0143835  0.0004553  31.590 < 0.0000000000000002 ***
## short_listTRUE 0.0031539  0.0005604   5.628         0.0000000183 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## 
## Topic 29:
## 
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)    
## (Intercept)    0.0198988  0.0005675   35.06 <0.0000000000000002 ***
## short_listTRUE 0.0087407  0.0007031   12.43 <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)    0.0396808  0.0003952  100.41 <0.0000000000000002 ***
## short_listTRUE 0.0072133  0.0004836   14.92 <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)    0.0327906  0.0004243  77.285 <0.0000000000000002 ***
## short_listTRUE 0.0010278  0.0005356   1.919               0.055 .  
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## 
## Topic 32:
## 
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)    
## (Intercept)    0.0267140  0.0003221  82.940 < 0.0000000000000002 ***
## short_listTRUE 0.0015707  0.0004060   3.869             0.000109 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## 
## Topic 33:
## 
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)    
## (Intercept)     0.0272215  0.0005582  48.763 <0.0000000000000002 ***
## short_listTRUE -0.0056705  0.0006372  -8.899 <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)     0.0323316  0.0005781   55.93 <0.0000000000000002 ***
## short_listTRUE -0.0127477  0.0007015  -18.17 <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)     0.0283380  0.0006976  40.619 <0.0000000000000002 ***
## short_listTRUE -0.0010562  0.0008695  -1.215               0.224
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 36:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0157139  0.0003743  41.985 < 0.0000000000000002 ***
## short_listTRUE 0.0015146  0.0004902   3.089              0.00201 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 37:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0236885  0.0003762   62.97 <0.0000000000000002 ***
## short_listTRUE 0.0061929  0.0004971   12.46 <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)     0.0280954  0.0003814   73.66 <0.0000000000000002 ***
## short_listTRUE -0.0065612  0.0005148  -12.74 <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)    0.0109084  0.0003918  27.839 < 0.0000000000000002 ***
## short_listTRUE 0.0038209  0.0004992   7.653   0.0000000000000198 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 40:
##
## Coefficients:
##                  Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0285280  0.0004104  69.513 <0.0000000000000002 ***
## short_listTRUE 0.0009296  0.0004707   1.975             0.0483 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 41:
##
## Coefficients:
##                   Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0259806  0.0005469  47.501 < 0.0000000000000002 ***
## short_listTRUE -0.0052569  0.0006507  -8.079 0.000000000000000663 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 42:
##
## Coefficients:
##                  Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0168810  0.0004296   39.30 <0.0000000000000002 ***
## short_listTRUE 0.0083489  0.0005809   14.37 <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)    0.0132724  0.0003954   33.57 <0.0000000000000002 ***
## short_listTRUE 0.0070828  0.0005324   13.30 <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)     0.0676859  0.0004198  161.23 <0.0000000000000002 ***
## short_listTRUE -0.0154128  0.0005234  -29.45 <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)     0.0168129  0.0003064  54.878 <0.0000000000000002 ***
## short_listTRUE -0.0005807  0.0003839  -1.512                0.13
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

# 3 Discussion

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

There is more gender distinction in some selected terms and topics. AWS MPs are far more likely to make reference to their constituency and their constituents. In the debate between whether MPs should be "delegates" or "trustees" – the "mandate-independence controversy" outlined by Pitkin (1967) – the references to their constituents and constituencies suggests AWS MPs shy away from the Burkean concept of trusteeship and see themselves more as strict representatives of their constituents. In Andeweg & Thomassen's (2005) typology of *ex ante*/*ex post* and above/below political representation, AWS MPs lean towards representation "from below", although their selection process is *ex ante*/*ex post*.

AWS MPs refer to their constituents both specifically and in the abstract, particularly when criticising government policy. For example, in debate on 4th March 2015, Gemma Doyle, 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

## 4.2 K30

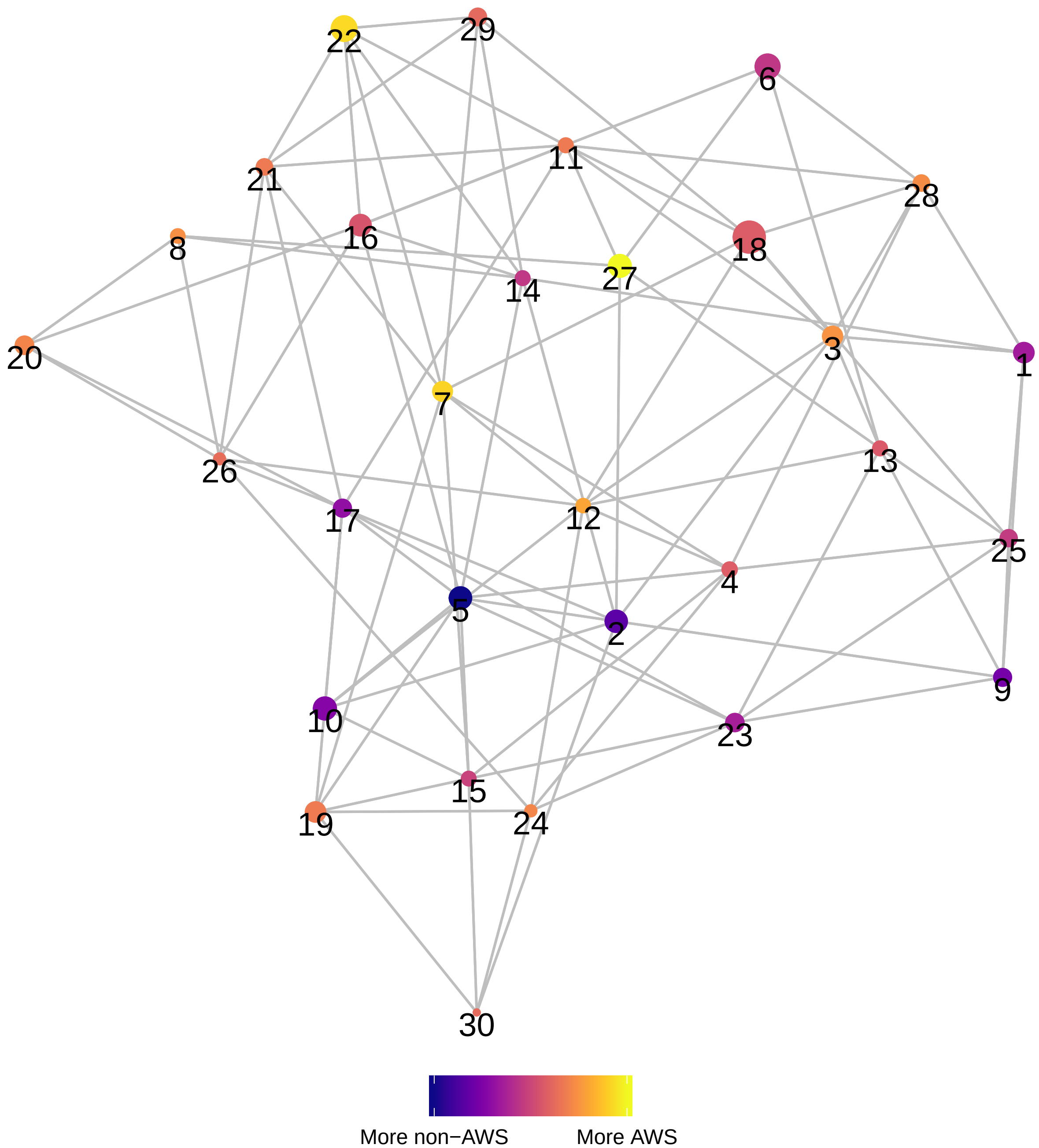


Figure 11: Fruchterman-Reingold plot of K30 Network

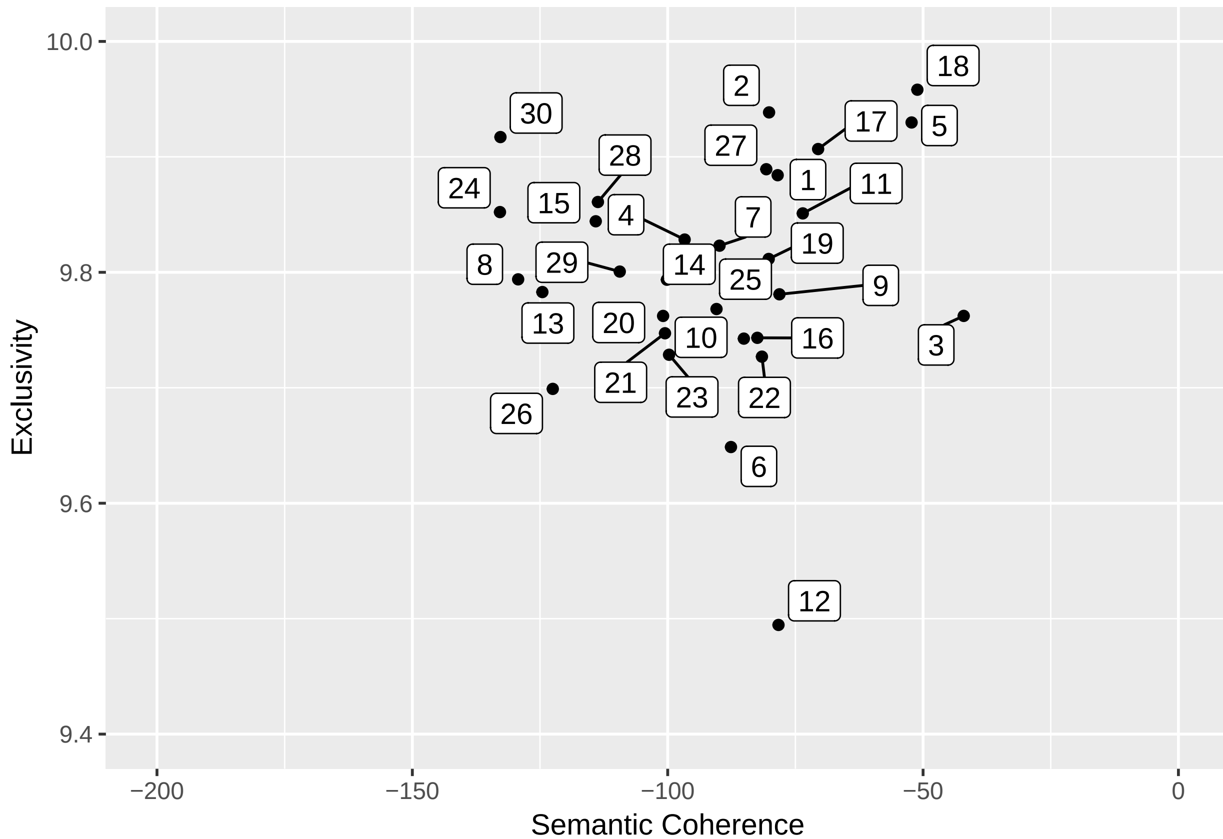


Figure 12: Coherence of K30 Topic Models

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

Table 13: Topic Estimates

| | Estimate | Standard Error | t value | Pr(>\|t\|) | |
|---|---|---|---|---|---|
| **Topic 1 – Bills** | | | | | |
| Intercept | 0.0458712 | 0.0006687 | 68.5967730 | < 0.001 | *** |
| Shortlist | -0.0075157 | 0.0008269 | -9.0888187 | < 0.001 | *** |
| **Topic 2 – Consultations** | | | | | |
| Intercept | 0.0649563 | 0.0005503 | 118.0343306 | < 0.001 | *** |
| Shortlist | -0.0140309 | 0.0006285 | -22.3234213 | < 0.001 | *** |
| **Topic 3 – Members** | | | | | |
| Intercept | 0.0399446 | 0.0005134 | 77.8024696 | < 0.001 | *** |
| Shortlist | 0.0062783 | 0.0006517 | 9.6344019 | < 0.001 | *** |
| **Topic 4 – Gender** | | | | | |
| Intercept | 0.0221288 | 0.0005909 | 37.4516418 | < 0.001 | *** |
| Shortlist | 0.0006035 | 0.0006962 | 0.8668347 | 0.39 | |
| **Topic 5 – Civic society** | | | | | |
| Intercept | 0.0713523 | 0.0005573 | 128.0428552 | < 0.001 | *** |
| Shortlist | -0.0196368 | 0.0006444 | -30.4737756 | < 0.001 | *** |
| **Topic 6 – International** | | | | | |

Table 13: Topic Estimates *(continued)*

| | Estimate | Standard Error | t value | Pr(>\|t\|) | |
|---|---|---|---|---|---|
| Intercept | 0.0459968 | 0.0008849 | 51.9825874 | < 0.001 | *** |
| Shortlist | -0.0041436 | 0.0011006 | -3.7650060 | < 0.001 | *** |
| **Topic 7 – Disability** | | | | | |
| Intercept | 0.0268169 | 0.0005674 | 47.2626207 | < 0.001 | *** |
| Shortlist | 0.0121432 | 0.0007535 | 16.1160112 | < 0.001 | *** |
| **Topic 8 – Rural Issues** | | | | | |
| Intercept | 0.0141966 | 0.0004702 | 30.1956254 | < 0.001 | *** |
| Shortlist | 0.0060430 | 0.0006038 | 10.0088599 | < 0.001 | *** |
| **Topic 9 – Immigration** | | | | | |
| Intercept | 0.0364745 | 0.0006414 | 56.8679257 | < 0.001 | *** |
| Shortlist | -0.0116333 | 0.0007598 | -15.3110110 | < 0.001 | *** |
| **Topic 10 – Health Care** | | | | | |
| Intercept | 0.0435391 | 0.0007381 | 58.9852893 | < 0.001 | *** |
| Shortlist | -0.0103242 | 0.0009364 | -11.0248381 | < 0.001 | *** |
| **Topic 11 – Parties** | | | | | |
| Intercept | 0.0318576 | 0.0004334 | 73.5007388 | < 0.001 | *** |
| Shortlist | 0.0036454 | 0.0005796 | 6.2895304 | < 0.001 | *** |
| **Topic 12 – Constituencies** | | | | | |
| Intercept | 0.0224602 | 0.0005105 | 43.9923920 | < 0.001 | *** |
| Shortlist | 0.0080669 | 0.0006417 | 12.5711053 | < 0.001 | *** |
| **Topic 13 – Security** | | | | | |
| Intercept | 0.0229229 | 0.0005022 | 45.6444006 | < 0.001 | *** |
| Shortlist | -0.0000187 | 0.0006082 | -0.0307897 | 0.98 | |
| **Topic 14 – Investment** | | | | | |
| Intercept | 0.0262868 | 0.0005331 | 49.3047507 | < 0.001 | *** |
| Shortlist | -0.0039607 | 0.0006502 | -6.0911071 | < 0.001 | *** |
| **Topic 15 – Youth** | | | | | |
| Intercept | 0.0229374 | 0.0005563 | 41.2335950 | < 0.001 | *** |
| Shortlist | -0.0027399 | 0.0006784 | -4.0386617 | < 0.001 | *** |
| **Topic 16 – Energy** | | | | | |
| Intercept | 0.0358344 | 0.0007108 | 50.4144444 | < 0.001 | *** |
| Shortlist | -0.0005301 | 0.0009133 | -0.5804305 | 0.56 | |
| **Topic 17 – Local authorities** | | | | | |
| Intercept | 0.0398938 | 0.0005175 | 77.0911318 | < 0.001 | *** |
| Shortlist | -0.0089663 | 0.0006147 | -14.5854986 | < 0.001 | *** |
| **Topic 18 – People** | | | | | |
| Intercept | 0.0846622 | 0.0005583 | 151.6480097 | < 0.001 | *** |
| Shortlist | 0.0003609 | 0.0007016 | 0.5143636 | 0.61 | |
| **Topic 19 – Education** | | | | | |
| Intercept | 0.0282652 | 0.0007088 | 39.8782762 | < 0.001 | *** |
| Shortlist | 0.0038531 | 0.0008284 | 4.6515266 | < 0.001 | *** |
| **Topic 20 – Transport** | | | | | |
| Intercept | 0.0228144 | 0.0005964 | 38.2503548 | < 0.001 | *** |
| Shortlist | 0.0049493 | 0.0007864 | 6.2932709 | < 0.001 | *** |
| **Topic 21 – Housing** | | | | | |
| Intercept | 0.0202289 | 0.0005974 | 33.8635917 | < 0.001 | *** |

Table 13: Topic Estimates *(continued)*

| | Estimate | Standard Error | t value | Pr(>\|t\|) | |
|---|---|---|---|---|---|
| Shortlist | 0.0037302 | 0.0007063 | 5.2816361 | < 0.001 | *** |
| **Topic 22 – Tax** | | | | | |
| Intercept | 0.0440624 | 0.0008150 | 54.0645801 | < 0.001 | *** |
| Shortlist | 0.0126805 | 0.0010399 | 12.1941360 | < 0.001 | *** |
| **Topic 23 – Police** | | | | | |
| Intercept | 0.0300247 | 0.0006072 | 49.4510917 | < 0.001 | *** |
| Shortlist | -0.0070468 | 0.0007877 | -8.9465204 | < 0.001 | *** |
| **Topic 24 – Media** | | | | | |
| Intercept | 0.0112192 | 0.0004444 | 25.2473086 | < 0.001 | *** |
| Shortlist | 0.0049904 | 0.0005075 | 9.8340202 | < 0.001 | *** |
| **Topic 25 – Families** | | | | | |
| Intercept | 0.0257938 | 0.0006263 | 41.1829844 | < 0.001 | *** |
| Shortlist | -0.0035639 | 0.0008010 | -4.4494426 | < 0.001 | *** |
| **Topic 26 – Environment** | | | | | |
| Intercept | 0.0145389 | 0.0004338 | 33.5173169 | < 0.001 | *** |
| Shortlist | 0.0022637 | 0.0005731 | 3.9497888 | < 0.001 | *** |
| **Topic 27 – Ministers** | | | | | |
| Intercept | 0.0419318 | 0.0005313 | 78.9270295 | < 0.001 | *** |
| Shortlist | 0.0151578 | 0.0006857 | 22.1040444 | < 0.001 | *** |
| **Topic 28 – Regions** | | | | | |
| Intercept | 0.0228703 | 0.0005291 | 43.2214145 | < 0.001 | *** |
| Shortlist | 0.0055559 | 0.0006821 | 8.1450003 | < 0.001 | *** |
| **Topic 29 – Pensions** | | | | | |
| Intercept | 0.0265448 | 0.0005760 | 46.0861797 | < 0.001 | *** |
| Shortlist | 0.0017499 | 0.0007287 | 2.4014058 | 0.016 | * |
| **Topic 30 – Technology** | | | | | |
| Intercept | 0.0135798 | 0.0003319 | 40.9146539 | < 0.001 | *** |
| Shortlist | 0.0020723 | 0.0004256 | 4.8692516 | < 0.001 | *** |

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

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

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

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

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

Table 15: Count and Distribution of Topics – K30

| Topic Number | AWS Speeches | Percent of AWS Speeches | Non-AWS Speeches | Percent of non-AWS Speeches | Male MP Speeches | Percent of Male MP Speeches |
|---|---|---|---|---|---|---|
| Bills | 1,819 | 3.38% | 1,263 | 4.53% | 8,176 | 4.83% |
| Consultations | 1,997 | 3.71% | 1,824 | 6.55% | 9,027 | 5.33% |
| Members | 2,146 | 3.99% | 844 | 3.03% | 8,694 | 5.13% |
| Gender | 1,039 | 1.93% | 553 | 1.98% | 882 | 0.52% |
| Civic society | 2,050 | 3.81% | 1,839 | 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% |
| 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 | 6,345 | 11.8% | 2,922 | 10.49% | 30,543 | 18.04% |

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

| Topic Number | AWS Speeches | Percent of AWS Speeches | Non-AWS Speeches | Percent of non-AWS Speeches | Male MP Speeches | Percent of Male MP Speeches |
|---|---|---|---|---|---|---|
| Education | 2,187 | 4.07% | 936 | 3.36% | 4,801 | 2.84% |
| Transport | 1,769 | 3.29% | 689 | 2.47% | 4,882 | 2.88% |
| Housing | 1,319 | 2.45% | 540 | 1.94% | 2,058 | 1.22% |
| Tax | 3,968 | 7.38% | 1,422 | 5.1% | 10,953 | 6.47% |
| Police | 1,425 | 2.65% | 971 | 3.48% | 3,523 | 2.08% |
| Media | 762 | 1.42% | 256 | 0.92% | 2,050 | 1.21% |
| Families | 1,271 | 2.36% | 791 | 2.84% | 1,112 | 0.66% |
| Environment | 712 | 1.32% | 282 | 1.01% | 1,706 | 1.01% |
| Ministers | 3,159 | 5.87% | 921 | 3.31% | 8,380 | 4.95% |
| Regions | 1,421 | 2.64% | 441 | 1.58% | 6,218 | 3.67% |
| Pensions | 1,445 | 2.69% | 723 | 2.59% | 3,022 | 1.78% |
| Technology | 502 | 0.93% | 177 | 0.64% | 1,149 | 0.68% |

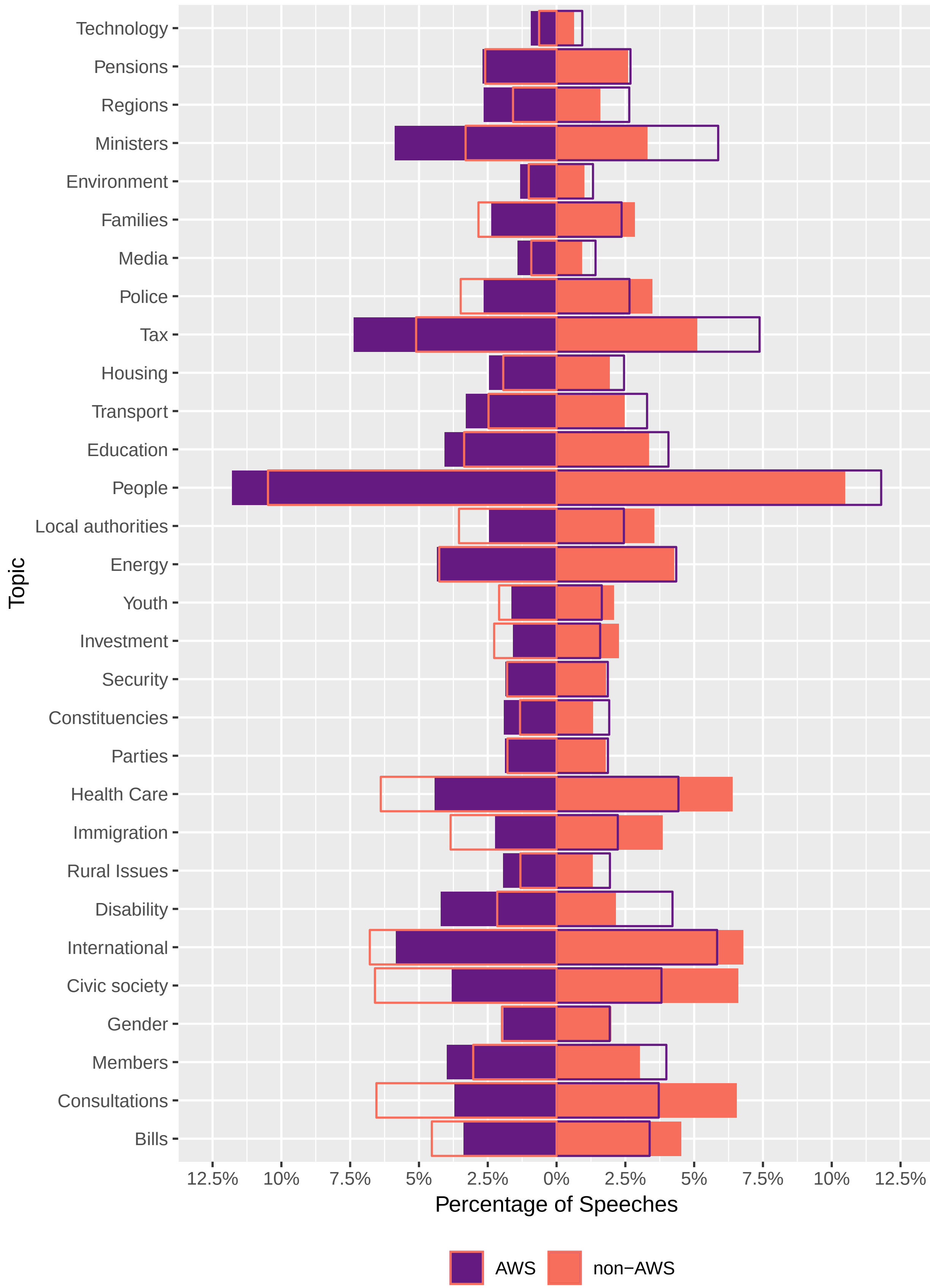


Figure 13: K30 Pyramid Chart

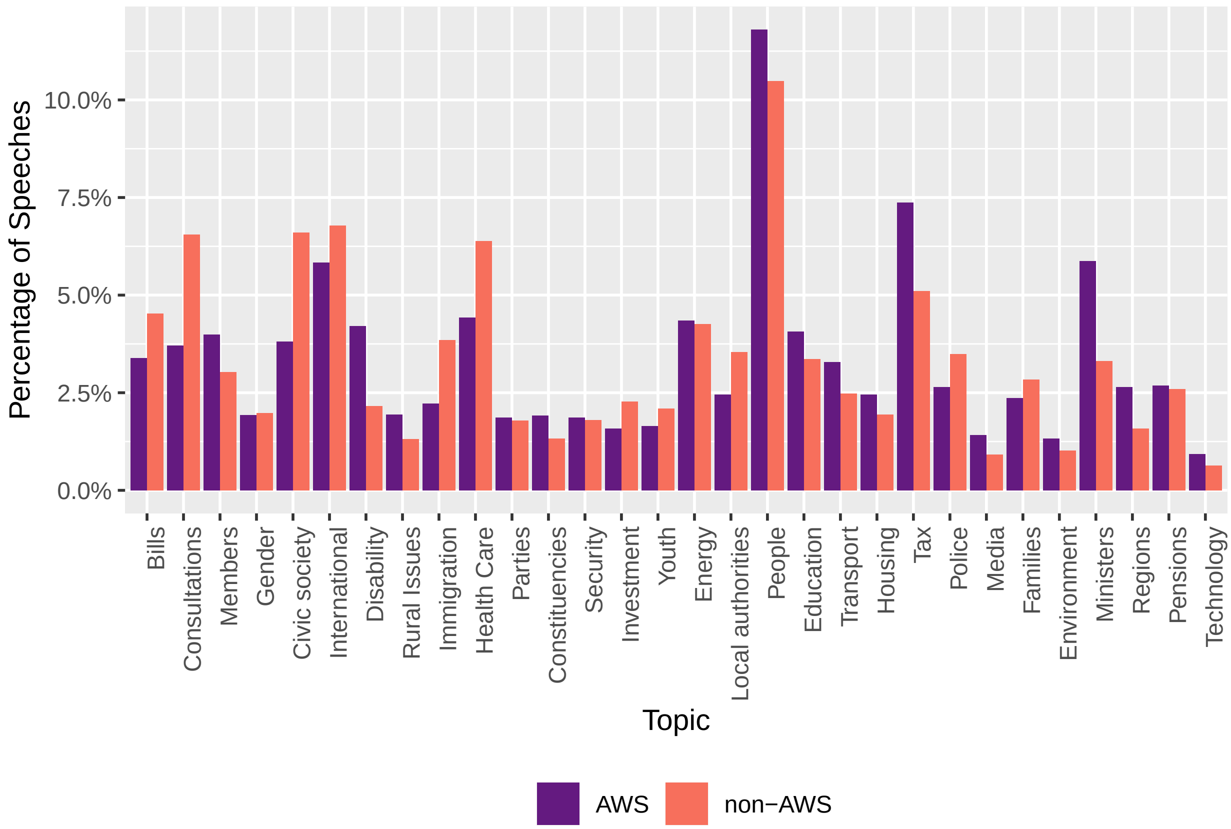


Figure 14: K30 Bar Chart

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

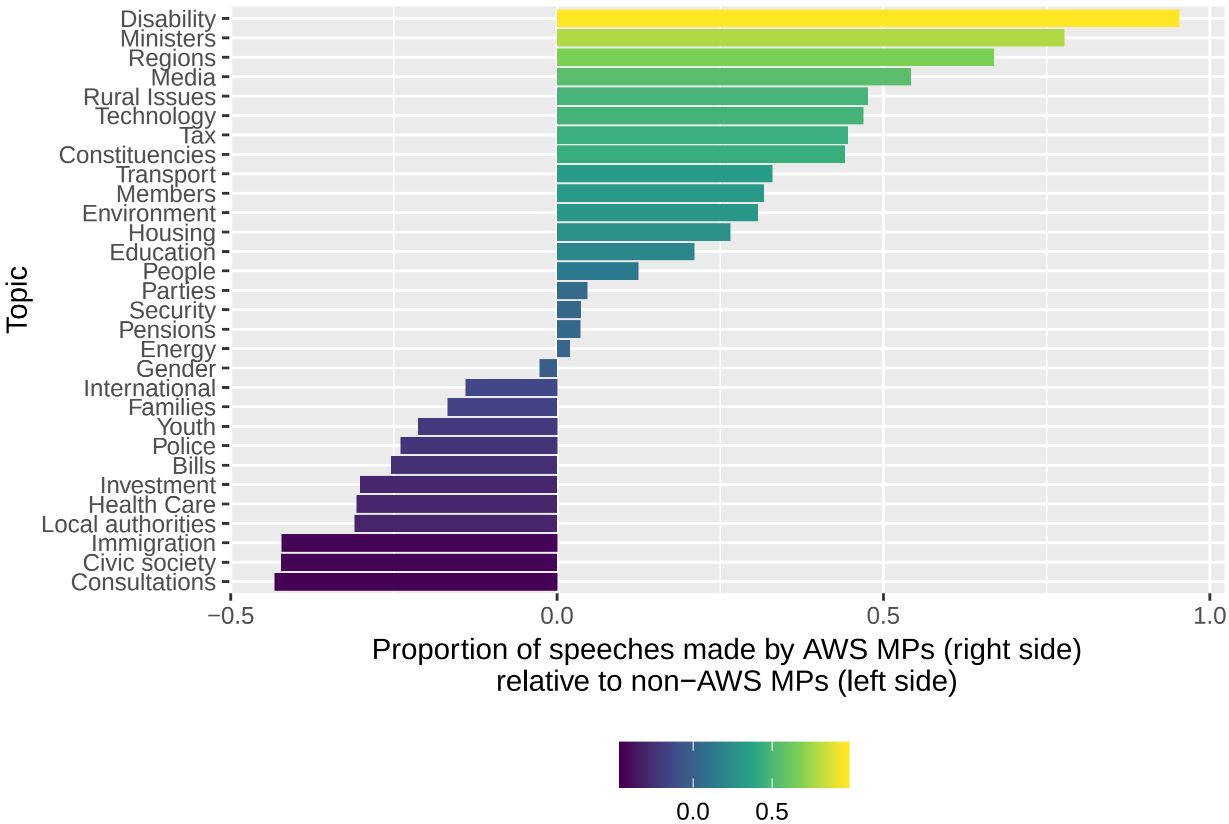


Figure 15: K30 Topic Proportions

#### 4.2.0.1 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 16: Words in Topic - K30

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

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

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

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

| Topic Number | Top Ten Words | Top Ten FREX |
|---|---|---|
| Topic 14 | companies, financial, company, market, business, public, bank, competition, regulation, sector, industry, banks, insurance, interest, consumers, accounts, private, treasury, regulatory, services | liabilities, policyholders, penrose, shareholders, regulators, auditor, accounting, competition, banking, oft, nao, corporate, comptroller, profits, shares, fsa, equitable, company's, cdc, rbs |
| Topic 15 | young, people, health, mental, youth, prison, drug, drugs, problems, age, services, 16, treatment, community, offenders, prisons, prisoners, can, suicide, use | prisons, probation, cannabis, reoffending, mental, self-harm, drug, prison, youth, drugs, young, prisoners, psychoactive, suicides, suicide, offending, psychiatric, rehabilitation, keynes, milton |
| Topic 16 | jobs, businesses, business, investment, economy, industry, energy, economic, new, small, growth, uk, future, change, climate, sector, government, skills, development, support | manufacturing, renewable, renewables, solar, low-carbon, carbon, onshore, climate, nissan, flood, steel, oil, biofuels, wind, emissions, businesses, apprentices, enterprise, energy-intensive, economy |
| Topic 17 | local, authorities, funding, areas, council, services, authority, community, area, communities, money, councils, million, new, social, needs, resources, fund, regional, planning | local, authorities, councils, funding, authority, formula, grant, areas, county, councillors, deprived, locally, council, allocated, allocation, partnerships, deprivation, surrey, lancashire, partnership |
| Topic 18 | people, want, one, can, get, say, know, think, us, make, many, need, go, time, much, just, see, point, said, take | things, think, say, something, want, going, get, lot, go, thing, trying, talking, really, saying, absolutely, quite, might, difficult, come, bit |
| Topic 19 | children, schools, education, school, child, parents, teachers, children's, training, skills, learning, needs, young, pupils, educational, care, special, provision, primary, good | teachers, pupils, curriculum, sen, academies, ofsted, pupil, grammar, attainment, vocational, classroom, fe, 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 16: Words in Topic - K30 *(continued)*

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

#### 4.2.1 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
```

#### 4.2.2 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)     0.0458704  0.0006695  68.512 <0.0000000000000002 ***
## short_listTRUE -0.0075086  0.0008280  -9.068 <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)     0.0649496  0.0005441  119.38 <0.0000000000000002 ***
## short_listTRUE -0.0140238  0.0006229  -22.52 <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)    0.0399419  0.0005173  77.210 <0.0000000000000002 ***
## short_listTRUE 0.0062753  0.0006533   9.605 <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  0.0005986  36.973 <0.0000000000000002 ***
## short_listTRUE 0.0006006  0.0006995   0.859               0.391
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 5:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0713433  0.0005514  129.40 <0.0000000000000002 ***
## short_listTRUE -0.0196229  0.0006432  -30.51 <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)     0.045995   0.000890  51.680 < 0.0000000000000002 ***
## short_listTRUE -0.004150   0.001108  -3.744             0.000181 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0268168  0.0005618   47.73 <0.0000000000000002 ***
## short_listTRUE 0.0121376  0.0007560   16.06 <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)    0.0141986  0.0004616   30.76 <0.0000000000000002 ***
## short_listTRUE 0.0060356  0.0005999   10.06 <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)     0.0364669  0.0006396   57.01 <0.0000000000000002 ***
## short_listTRUE -0.0116329  0.0007588  -15.33 <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)     0.0435336  0.0007358   59.17 <0.0000000000000002 ***
## short_listTRUE -0.0103227  0.0009207  -11.21 <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)    0.0318534  0.0004357  73.110 < 0.0000000000000002 ***
## short_listTRUE 0.0036483  0.0005811   6.278       0.000000000344 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 12:
```

```
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0224519  0.0005153   43.57 <0.0000000000000002 ***
## short_listTRUE 0.0080737  0.0006433   12.55 <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)     0.02292617  0.00049834  46.005 <0.0000000000000002 ***
## short_listTRUE -0.00002093  0.00060587  -0.035               0.972
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0262823  0.0005314  49.459 < 0.0000000000000002 ***
## short_listTRUE -0.0039574  0.0006547  -6.045         0.0000000015 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0229382  0.0005664  40.500 < 0.0000000000000002 ***
## short_listTRUE -0.0027425  0.0006936  -3.954             0.000077 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 16:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0358333  0.0007049  50.832 <0.0000000000000002 ***
## short_listTRUE -0.0005362  0.0009124  -0.588               0.557
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 17:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0398880  0.0005133   77.71 <0.0000000000000002 ***
```

```
## short_listTRUE -0.0089577  0.0006104  -14.67 <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)    0.0846628  0.0005563 152.196 <0.0000000000000002 ***
## short_listTRUE 0.0003553  0.0007006   0.507               0.612
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 19:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0282624  0.0006975  40.522 < 0.0000000000000002 ***
## short_listTRUE 0.0038451  0.0008289   4.639           0.00000351 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0228238  0.0006005  38.006 < 0.0000000000000002 ***
## short_listTRUE 0.0049424  0.0007851   6.295       0.000000000309 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0202244  0.0005977  33.840 < 0.0000000000000002 ***
## short_listTRUE 0.0037387  0.0007003   5.338          0.000000094 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 22:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0440592  0.0008083   54.51 <0.0000000000000002 ***
## short_listTRUE 0.0126838  0.0010308   12.30 <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)     0.0300328  0.0006096  49.263 <0.0000000000000002 ***
## short_listTRUE -0.0070665  0.0007944  -8.895 <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)    0.0112201  0.0004404  25.475 <0.0000000000000002 ***
## short_listTRUE 0.0049891  0.0005043   9.893 <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)     0.0257951  0.0006224  41.444 < 0.0000000000000002 ***
## short_listTRUE -0.0035651  0.0007985  -4.465           0.00000803 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0145462  0.0004389  33.143 < 0.0000000000000002 ***
## short_listTRUE 0.0022597  0.0005701   3.964            0.0000739 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0419220  0.0005363   78.16 <0.0000000000000002 ***
## short_listTRUE 0.0151747  0.0006886   22.04 <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)    0.0228763  0.0005312  43.066 < 0.0000000000000002 ***
## short_listTRUE 0.0055464  0.0006802   8.154 0.000000000000000358 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0265499  0.0005796   45.80 <0.0000000000000002 ***
## short_listTRUE 0.0017402  0.0007281    2.39              0.0168 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 30:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0135774  0.0003273  41.489 < 0.0000000000000002 ***
## short_listTRUE 0.0020772  0.0004225   4.916          0.000000885 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

### 4.3 K60

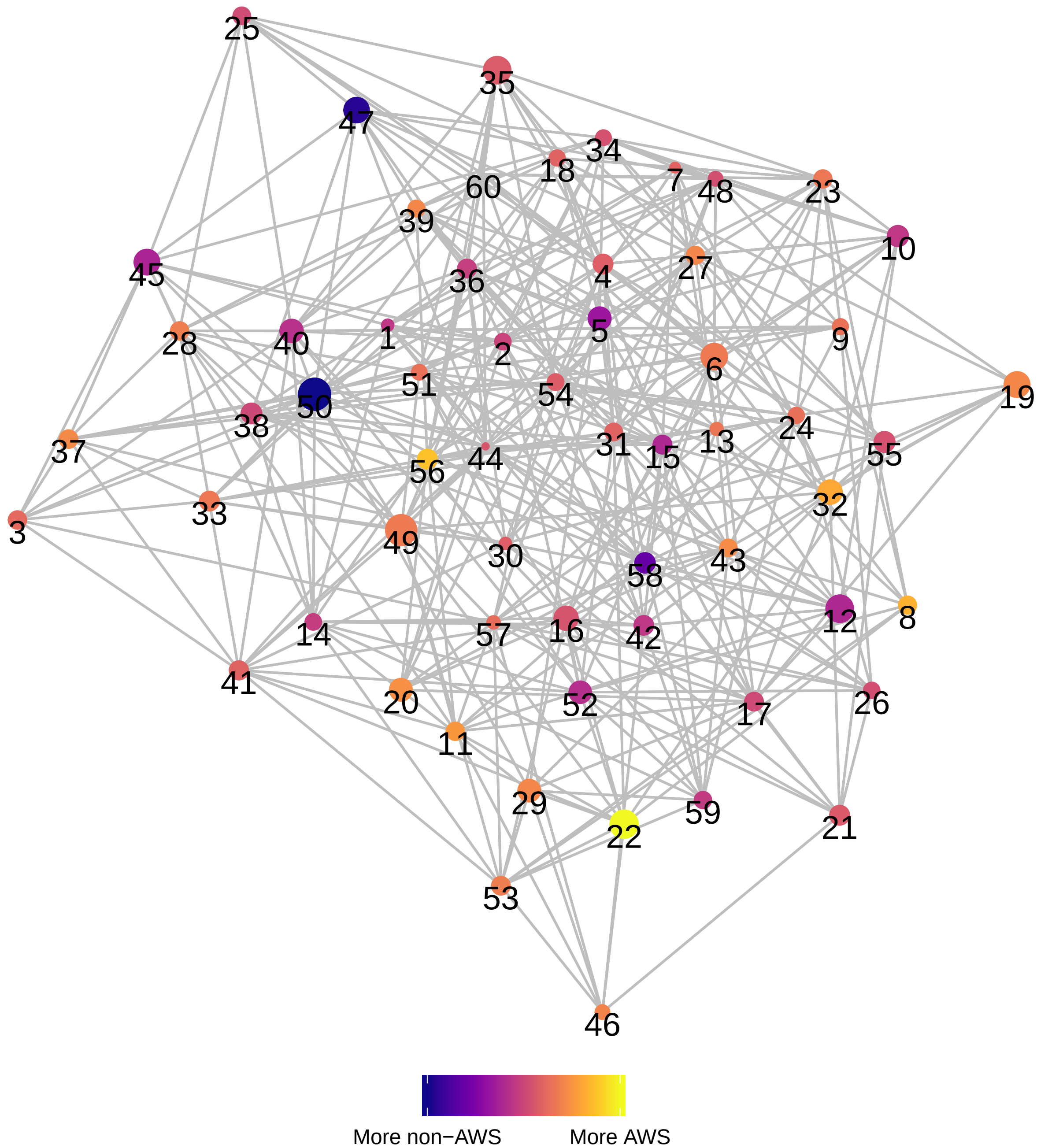


Figure 16: Fruchterman-Reingold plot of K60 Network

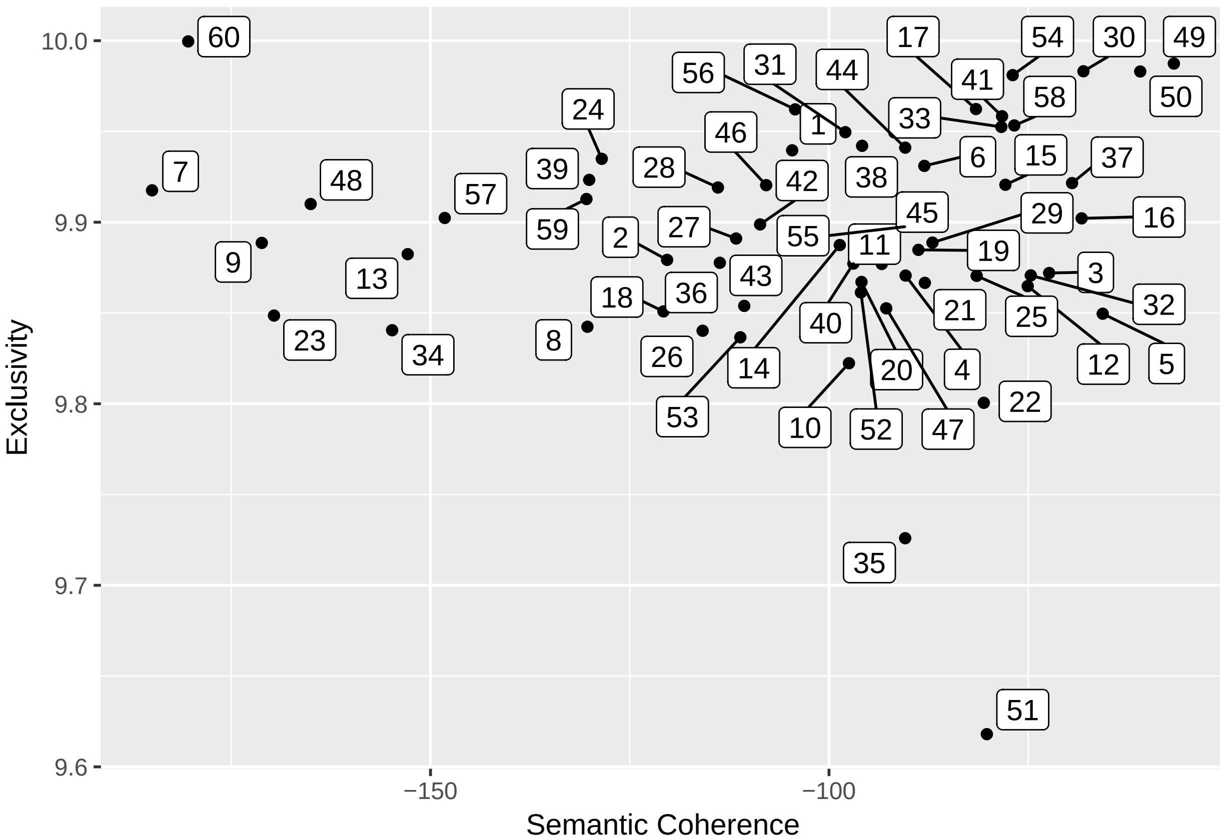


Figure 17: Coherence of K60 Topic Models

Table 17: Count and Distribution of Topics – K60

| Topic Number | AWS Speeches | Percent of AWS Speeches | Non-AWS Speeches | Percent of non-AWS Speeches | Male MP Speeches | Percent of Male MP Speeches |
|---|---|---|---|---|---|---|
| Topic 1 | 184 | 0.34% | 150 | 0.54% | 540 | 0.32% |
| Topic 2 | 543 | 1.01% | 210 | 0.75% | 1,526 | 0.9% |
| Topic 3 | 689 | 1.28% | 341 | 1.22% | 3,046 | 1.8% |
| Topic 4 | 821 | 1.53% | 447 | 1.6% | 301 | 0.18% |
| Topic 5 | 1,122 | 2.09% | 796 | 2.86% | 3,005 | 1.77% |
| Topic 6 | 2,029 | 3.77% | 786 | 2.82% | 4,255 | 2.51% |
| Topic 7 | 168 | 0.31% | 60 | 0.22% | 175 | 0.1% |
| Topic 8 | 837 | 1.56% | 143 | 0.51% | 1,734 | 1.02% |
| Topic 9 | 501 | 0.93% | 183 | 0.66% | 1,630 | 0.96% |
| Topic 10 | 890 | 1.65% | 656 | 2.35% | 1,418 | 0.84% |
| Topic 11 | 752 | 1.4% | 264 | 0.95% | 1,575 | 0.93% |
| Topic 12 | 1,905 | 3.54% | 1,212 | 4.35% | 4,343 | 2.56% |
| Topic 13 | 307 | 0.57% | 91 | 0.33% | 534 | 0.32% |
| Topic 14 | 432 | 0.8% | 328 | 1.18% | 1,389 | 0.82% |
| Topic 15 | 660 | 1.23% | 440 | 1.58% | 2,102 | 1.24% |
| Topic 16 | 1,434 | 2.67% | 789 | 2.83% | 5,056 | 2.99% |
| Topic 17 | 677 | 1.26% | 405 | 1.45% | 2,867 | 1.69% |

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

| Topic Number | AWS Speeches | Percent of AWS Speeches | Non-AWS Speeches | Percent of non-AWS Speeches | Male MP Speeches | Percent of Male MP Speeches |
|---|---|---|---|---|---|---|
| Topic 18 | 484 | 0.9% | 227 | 0.81% | 904 | 0.53% |
| Topic 19 | 1,872 | 3.48% | 773 | 2.77% | 5,577 | 3.29% |
| Topic 20 | 1,391 | 2.59% | 498 | 1.79% | 3,654 | 2.16% |
| Topic 21 | 839 | 1.56% | 449 | 1.61% | 1,385 | 0.82% |
| Topic 22 | 2,584 | 4.8% | 748 | 2.68% | 6,015 | 3.55% |
| Topic 23 | 724 | 1.35% | 282 | 1.01% | 1,434 | 0.85% |
| Topic 24 | 523 | 0.97% | 198 | 0.71% | 1,541 | 0.91% |
| Topic 25 | 554 | 1.03% | 363 | 1.3% | 995 | 0.59% |
| Topic 26 | 483 | 0.9% | 257 | 0.92% | 1,218 | 0.72% |
| Topic 27 | 709 | 1.32% | 276 | 0.99% | 1,627 | 0.96% |
| Topic 28 | 777 | 1.44% | 252 | 0.9% | 3,762 | 2.22% |
| Topic 29 | 1,333 | 2.48% | 514 | 1.84% | 2,903 | 1.71% |
| Topic 30 | 232 | 0.43% | 96 | 0.34% | 882 | 0.52% |
| Topic 31 | 594 | 1.1% | 328 | 1.18% | 1,973 | 1.17% |
| Topic 32 | 1,719 | 3.2% | 538 | 1.93% | 2,452 | 1.45% |
| Topic 33 | 962 | 1.79% | 305 | 1.09% | 3,374 | 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% | 415 | 1.49% | 3,874 | 2.29% |
| Topic 42 | 699 | 1.3% | 545 | 1.96% | 1,588 | 0.94% |
| Topic 43 | 685 | 1.27% | 215 | 0.77% | 1,466 | 0.87% |
| Topic 44 | 105 | 0.2% | 36 | 0.13% | 100 | 0.06% |
| Topic 45 | 1,572 | 2.92% | 1,029 | 3.69% | 7,673 | 4.53% |
| Topic 46 | 449 | 0.83% | 96 | 0.34% | 522 | 0.31% |
| Topic 47 | 1,183 | 2.2% | 1,352 | 4.85% | 4,523 | 2.67% |
| Topic 48 | 322 | 0.6% | 222 | 0.8% | 409 | 0.24% |
| Topic 49 | 3,174 | 5.9% | 1,095 | 3.93% | 16,080 | 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% | 2,569 | 1.52% |
| Topic 59 | 459 | 0.85% | 411 | 1.48% | 1,696 | 1% |

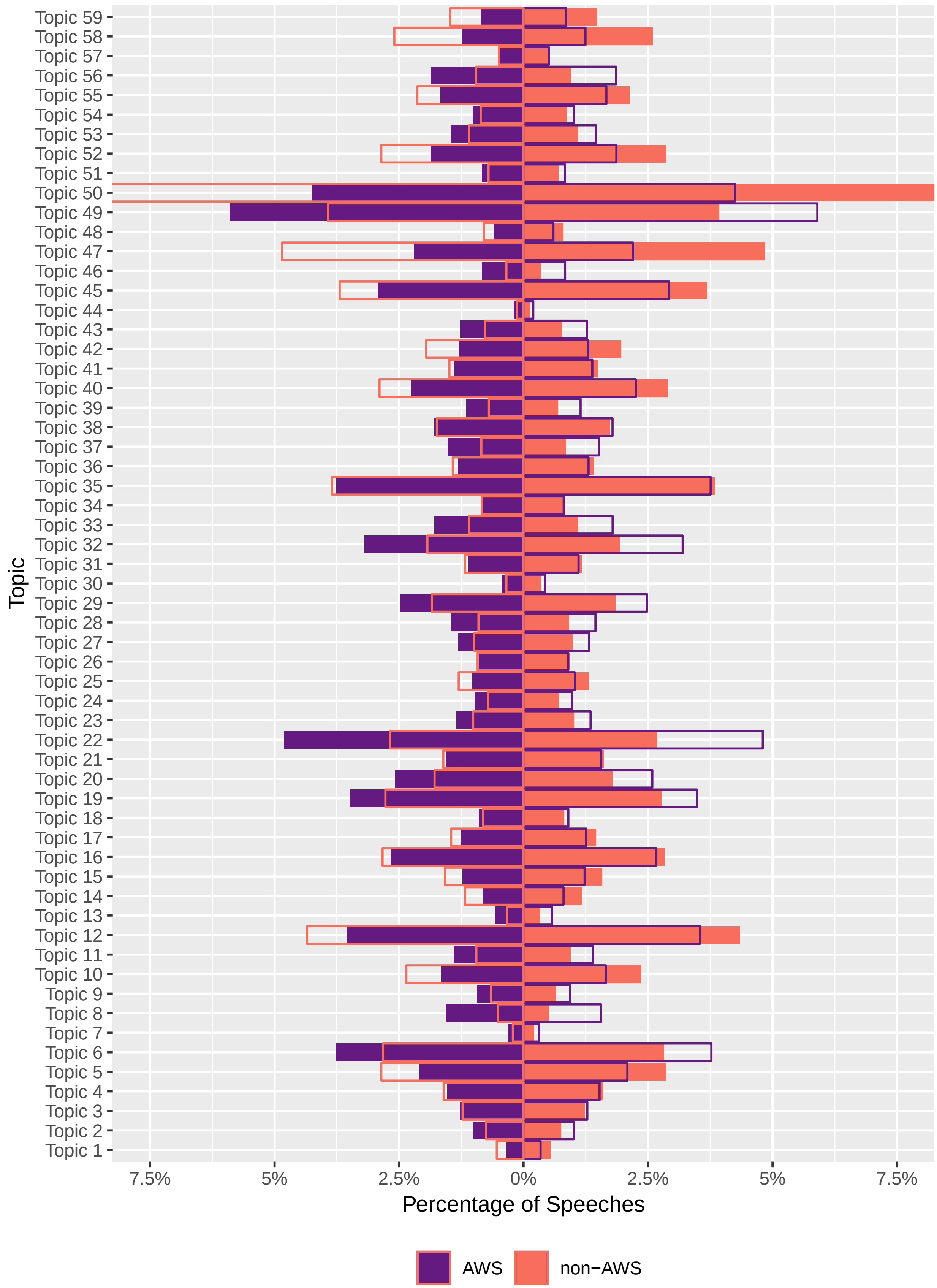


Figure 18: K60 Pyramid Chart

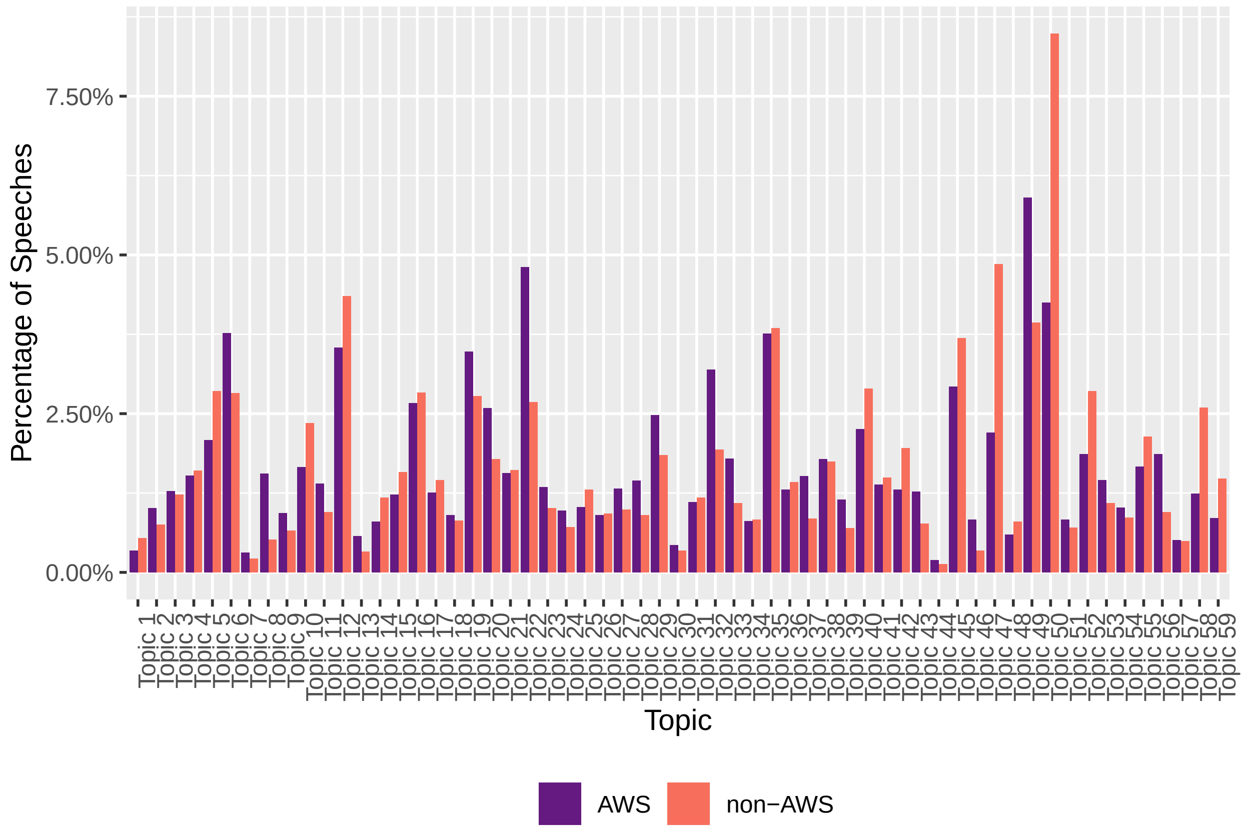


Figure 19: K60 Bar Chart

#### 4.3.0.1 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 18: Words in topic - K60

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

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

| Topic Number | Top Ten Words | Top Ten FREX |
|---|---|---|
| Topic 3 | member, members, said, made, north, heard, spoke, also, debate, friends, speech, south, east, mentioned, talked, raised, west, pointed, many, comments | member, thoughtful, spoke, eastmr, hayes, eloquently, southmr, westmr, redwood, bermondsey, northmr, talked, holborn, wokinghammr, rushcliffemr, durhammr, norfolkmr, harlingtonjohn, valleymr, dorsetmr |
| Topic 4 | women, violence, men, domestic, women's, pay, woman, work, girls, equal, gender, gap, female, equality, sexual, male, many, maternity, still, victims | women, fgm, women's, shortlists, men, male, female, violence, girls, domestic, gender, paternity, woman, refuges, men's, maternity, all-women, pregnant, sanitary, refuge |
| Topic 5 | police, crime, officers, behaviour, policing, antisocial, home, community, people, tackle, force, forces, powers, communities, serious, neighbourhood, chief, streets, officer, support | policing, antisocial, police, crime, officers, pcsos, behaviour, constable, graffiti, asbos, soca, neighbourhood, gang, constabulary, knife, cctv, constables, gangs, burglary, wardens |
| Topic 6 | made, make, department, progress, taking, recent, ensure, action, assessment, impact, government, steps, statement, discussions, plans, strategy, development, northern, commitment, measures | progress, steps, discussions, assessment, taking, department, recent, strategy, northern, representations, developing, action, plans, statement, department's, ireland, implementation, priority, targets, departmental |
| Topic 7 | hearing, touch, aids, people, hiv, database, dna, blind, deaf, can, also, copyright, loss, helpline, 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 18: Words in topic - K60 *(continued)*

| Topic Number | Top Ten Words | Top Ten FREX |
|---|---|---|
| Topic 12 | care, health, nhs, services, hospital, patients, service, social, trust, hospitals, staff, trusts, patient, need, primary, people, nurses, waiting, community, e | helier, hospitals, pct, nhs, hospital, trusts, e, nursing, commissioning, dementia, beds, gp, acute, pharmacies, patients, nurses, pcts, patient, midwives, in-patient |
| Topic 13 | emergency, fire, service, phone, mobile, calls, john, ambulance, rescue, sir, public, incident, call, incidents, services, phones, blood, ms, lives, firefighters | firefighters, fire, phones, cpr, mobile, phone, rescue, ambulance, masts, fires, coastguard, emergency, ms, ambulances, john, crews, paramedics, emergencies, gannet, clyde |
| Topic 14 | companies, company, tax, competition, financial, market, consumers, uk, industry, regime, rules, fair, business, public, fsa, services, regulatory, transparency, profits, trading | fsa, competition, hmrc, corporate, policyholders, liabilities, shares, avoidance, shareholders, dependencies, evasion, penrose, regulators, liability, company's, companies, oft, company, equitable, directors |
| Topic 15 | community, organisations, work, role, services, voluntary, support, public, social, groups, sector, important, programme, working, service, together, play, good, society, project | voluntary, organisations, bbc, programmes, role, play, project, organisation, exclusion, innovative, radio, groups, community, initiatives, volunteers, volunteering, bristol, ideas, develop, charter |
| Topic 16 | jobs, economy, economic, investment, growth, industry, regional, future, new, development, need, skills, uk, manufacturing, country, sector, world, north-east, infrastructure, region | manufacturing, steel, economy, growth, regional, economic, jobs, productivity, economies, north-east, prosperity, regions, industries, inward, recession, region, construction, investment, downturn, invest |
| Topic 17 | million, funding, money, increase, billion, extra, year, additional, fund, spending, cost, costs, investment, resources, budget, spent, 1, new, funds, next | funding, million, expenditure, formula, extra, billion, grant, spent, fund, allocated, money, spending, funds, additional, funded, spend, invested, allocation, plymouth, 2007-08 |
| Topic 18 | communities, black, language, minority, community, church, ethnic, faith, people, country, religious, english, many, groups, forced, prevent, muslim, marriage, freedom, hate | sikh, hatred, muslim, humanist, holocaust, islam, ethnic, extremism, church, racism, asian, black, hate, religious, muslims, faith, faiths, priests, minority, minorities |
| Topic 19 | education, schools, school, children, teachers, students, skills, pupils, educational, learning, special, parents, college, primary, needs, university, training, good, standards, higher | teachers, pupils, curriculum, sen, academies, ofsted, pupil, grammar, schools, fe, 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 18: Words in topic - K60 *(continued)*

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

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

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

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

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

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

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

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

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

### 4.3.1 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
```

```
##       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, inters
##       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
```

```
##       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)     0.013033   0.000290  44.940 <0.0000000000000002 ***
## short_listTRUE -0.003122   0.000334  -9.348 <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)     0.0121059  0.0003358  36.048 < 0.0000000000000002 ***
## short_listTRUE -0.0020852  0.0004274  -4.879           0.00000107 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0167119  0.0003696  45.215 <0.0000000000000002 ***
## short_listTRUE 0.0011223  0.0004225   2.656              0.0079 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0140764  0.0004815  29.236 <0.0000000000000002 ***
## short_listTRUE 0.0002091  0.0005554   0.377               0.706
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 5:
```

```
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0210695  0.0005063   41.61 <0.0000000000000002 ***
## short_listTRUE -0.0060125  0.0006148   -9.78 <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)    0.0255938  0.0004068  62.910 < 0.0000000000000002 ***
## short_listTRUE 0.0025403  0.0005308   4.786           0.00000171 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0039769  0.0001842  21.595 < 0.0000000000000002 ***
## short_listTRUE 0.0007478  0.0002314   3.232              0.00123 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 8:
##
## Coefficients:
##                Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0061473  0.0003454   17.80 <0.0000000000000002 ***
## short_listTRUE 0.0064980  0.0004831   13.45 <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)    0.0062949  0.0003194  19.710 < 0.0000000000000002 ***
## short_listTRUE 0.0019990  0.0003973   5.031          0.000000488 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0175441  0.0004551  38.548 < 0.0000000000000002 ***
```

```
## short_listTRUE -0.0031669  0.0005660  -5.596         0.000000022 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0108547  0.0003357   32.33 <0.0000000000000002 ***
## short_listTRUE 0.0047560  0.0004012   11.85 <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)     0.0263115  0.0006027   43.65 < 0.0000000000000002 ***
## short_listTRUE -0.0045678  0.0007059   -6.47      0.0000000000982 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0053959  0.0002677  20.155 < 0.0000000000000002 ***
## short_listTRUE 0.0022134  0.0003262   6.786      0.0000000000116 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0131850  0.0003517  37.491 < 0.0000000000000002 ***
## short_listTRUE -0.0025206  0.0004267  -5.907        0.00000000349 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0226983  0.0004270  53.156 <0.0000000000000002 ***
## short_listTRUE -0.0045711  0.0004718  -9.689 <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)     0.0218688  0.0004845  45.136 <0.0000000000000002 ***
## short_listTRUE -0.0006678  0.0005791  -1.153               0.249
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 17:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0203197  0.0003539  57.415 < 0.0000000000000002 ***
## short_listTRUE -0.0015002  0.0004221  -3.554              0.00038 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0089807  0.0003485  25.769 <0.0000000000000002 ***
## short_listTRUE 0.0006005  0.0004105   1.463               0.143
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 19:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0190554  0.0005365   35.52 < 0.0000000000000002 ***
## short_listTRUE 0.0035203  0.0006889    5.11          0.000000323 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0136556  0.0005004  27.288 < 0.0000000000000002 ***
## short_listTRUE 0.0042650  0.0006756   6.313       0.000000000275 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:
```

```
##                  Estimate Std. Error t value           Pr(>|t|)
## (Intercept)     0.0132521  0.0004078  32.497 <0.0000000000000002 ***
## short_listTRUE -0.0001370  0.0005183  -0.264               0.792
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 22:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0196851  0.0005850   33.65 <0.0000000000000002 ***
## short_listTRUE 0.0108642  0.0007227   15.03 <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)    0.0092228  0.0004309  21.404 < 0.0000000000000002 ***
## short_listTRUE 0.0023013  0.0005414   4.251            0.0000213 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0075411  0.0003092  24.393 < 0.0000000000000002 ***
## short_listTRUE 0.0017586  0.0003627   4.848           0.00000125 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 25:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0131931  0.0004223  31.239 < 0.0000000000000002 ***
## short_listTRUE -0.0013621  0.0004803  -2.836              0.00457 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0103603  0.0003363  30.807 < 0.0000000000000002 ***
## short_listTRUE -0.0011148  0.0004311  -2.586              0.00971 **
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0116708  0.0003873   30.13 < 0.0000000000000002 ***
## short_listTRUE 0.0034830  0.0004601    7.57   0.0000000000000378 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 28:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0109647  0.0003374  32.500 < 0.0000000000000002 ***
## short_listTRUE 0.0028709  0.0004118   6.971     0.00000000000316 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0170793  0.0004539  37.625 < 0.0000000000000002 ***
## short_listTRUE 0.0034736  0.0005954   5.834        0.00000000544 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 30:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0213884  0.0001846 115.886 <0.0000000000000002 ***
## short_listTRUE 0.0002565  0.0002426   1.057                0.29
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 31:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0208893  0.0003020  69.162 <0.0000000000000002 ***
## short_listTRUE 0.0005422  0.0003628   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)    0.0196010  0.0004494   43.62 <0.0000000000000002 ***
## short_listTRUE 0.0058560  0.0005089   11.51 <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)    0.0154494  0.0003299  46.835 < 0.0000000000000002 ***
## short_listTRUE 0.0023208  0.0003837   6.049        0.00000000147 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 34:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0096922  0.0003748  25.861 <0.0000000000000002 ***
## short_listTRUE -0.0008223  0.0004491  -1.831              0.0671 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 35:
##
## Coefficients:
##                  Estimate  Std. Error t value            Pr(>|t|)
## (Intercept)     0.02396505  0.00063435  37.779 <0.0000000000000002 ***
## short_listTRUE -0.00005179  0.00080734  -0.064               0.949
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 36:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0160722  0.0004417  36.388 < 0.0000000000000002 ***
## short_listTRUE -0.0024413  0.0005356  -4.558           0.00000517 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 37:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0168701  0.0002537   66.50 <0.0000000000000002 ***
```

```
## short_listTRUE 0.0037585  0.0003284   11.44 <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)     0.0239549  0.0003882  61.710 < 0.0000000000000002 ***
## short_listTRUE -0.0016699  0.0004805  -3.476              0.00051 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 39:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0075348  0.0003300  22.835 <0.0000000000000002 ***
## short_listTRUE 0.0035161  0.0003941   8.923 <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)     0.0220773  0.0004734   46.63 < 0.0000000000000002 ***
## short_listTRUE -0.0036907  0.0005525   -6.68       0.000000000024 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 41:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0246498  0.0002801  87.995 <0.0000000000000002 ***
## short_listTRUE 0.0005358  0.0003623   1.479               0.139
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 42:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0176345  0.0004569  38.599 < 0.0000000000000002 ***
## short_listTRUE -0.0031268  0.0005308  -5.891        0.00000000386 ***
## ---
## 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  0.0004177  28.132 < 0.0000000000000002 ***
## short_listTRUE 0.0038099  0.0005147   7.402    0.000000000000136 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 44:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0091581  0.0001386  66.093 < 0.0000000000000002 ***
## short_listTRUE -0.0004892  0.0001680  -2.912              0.00359 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 45:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0318756  0.0006173   51.63 < 0.0000000000000002 ***
## short_listTRUE -0.0048638  0.0007529   -6.46       0.000000000105 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 46:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0066491  0.0002665  24.952 <0.0000000000000002 ***
## short_listTRUE 0.0033259  0.0003482   9.551 <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)     0.0307985  0.0005942   51.83 <0.0000000000000002 ***
## short_listTRUE -0.0133691  0.0007729  -17.30 <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)     0.0086541  0.0003011  28.738 < 0.0000000000000002 ***
## short_listTRUE -0.0009993  0.0003686  -2.711              0.00671 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 49:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0438277  0.0003997 109.649 < 0.0000000000000002 ***
## short_listTRUE 0.0026589  0.0004686   5.674          0.000000014 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 50:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0557500  0.0003557  156.75 <0.0000000000000002 ***
## short_listTRUE -0.0144800  0.0004331  -33.43 <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)    0.0099028  0.0003715   26.66 <0.0000000000000002 ***
## short_listTRUE 0.0017927  0.0004609    3.89              0.0001 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 52:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0184083  0.0005258  35.013 < 0.0000000000000002 ***
## short_listTRUE -0.0039593  0.0006859  -5.773        0.00000000782 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 53:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0110233  0.0003880  28.411 < 0.0000000000000002 ***
## short_listTRUE 0.0028311  0.0004779   5.924        0.00000000316 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 54:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0266578  0.0002043  130.51 <0.0000000000000002 ***
## short_listTRUE 0.0001306  0.0002511    0.52               0.603
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 55:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0174579  0.0004944  35.315 <0.0000000000000002 ***
## short_listTRUE -0.0008204  0.0005934  -1.382               0.167
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 56:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0165683  0.0003148   52.63 <0.0000000000000002 ***
## short_listTRUE 0.0075559  0.0003993   18.92 <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)    0.0066541  0.0002759  24.119 < 0.0000000000000002 ***
## short_listTRUE 0.0014066  0.0003393   4.146            0.0000339 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 58:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0270025  0.0003698   73.03 <0.0000000000000002 ***
## short_listTRUE -0.0097553  0.0004520  -21.58 <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)     0.0123941  0.0003540  35.010 < 0.0000000000000002 ***
## short_listTRUE -0.0027862  0.0004022  -6.928     0.00000000000431 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 60:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.00382563 0.00003757  101.83 <0.0000000000000002 ***
## short_listTRUE 0.00064418 0.00004683   13.76 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## 4.4 K0

### 4.4.1 Shortlists vs Non-Shortlists - k0

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

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

THIS NEEDS TO BE RUN

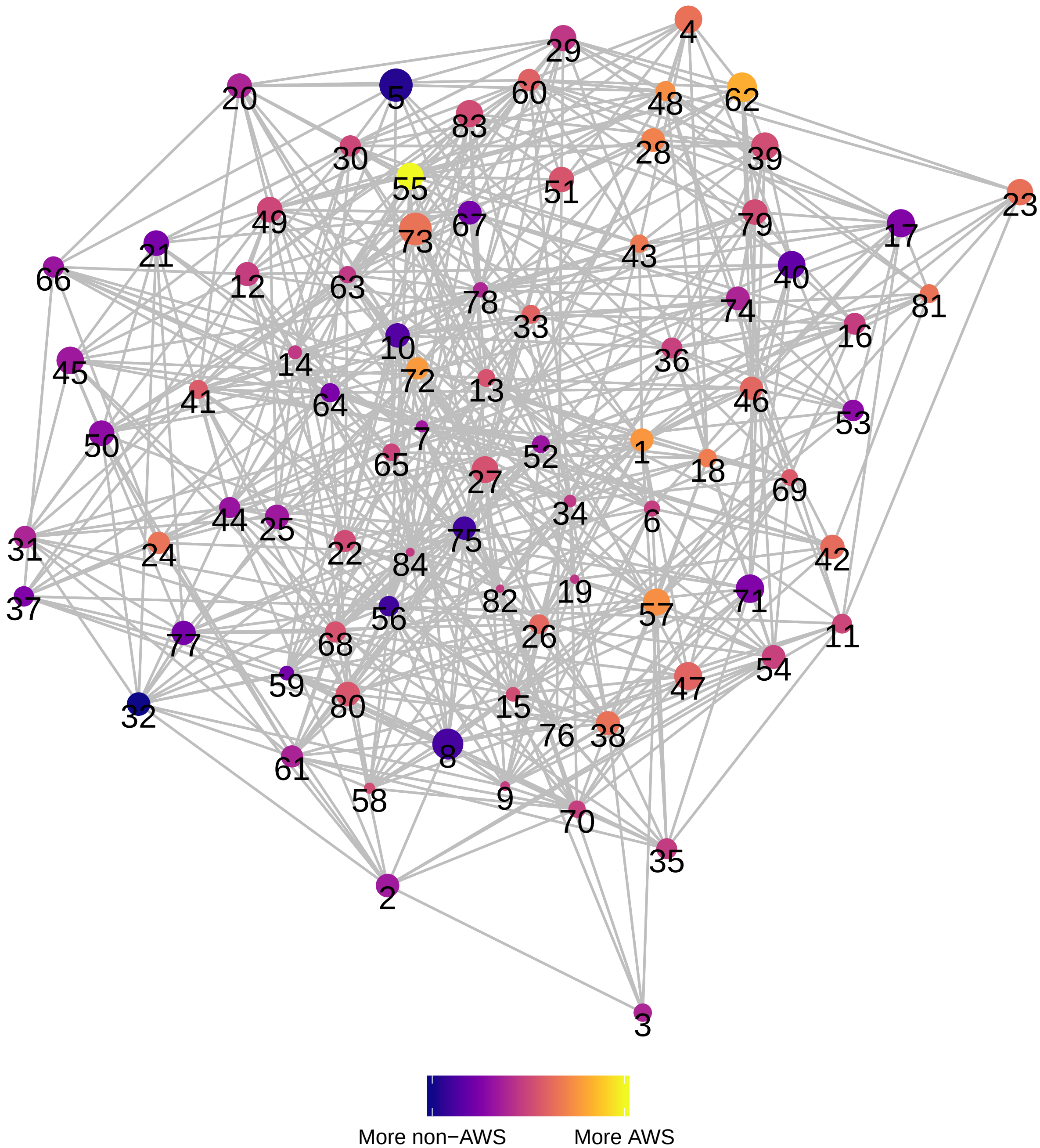


Figure 20: Fruchterman-Reingold plot of k0 Network

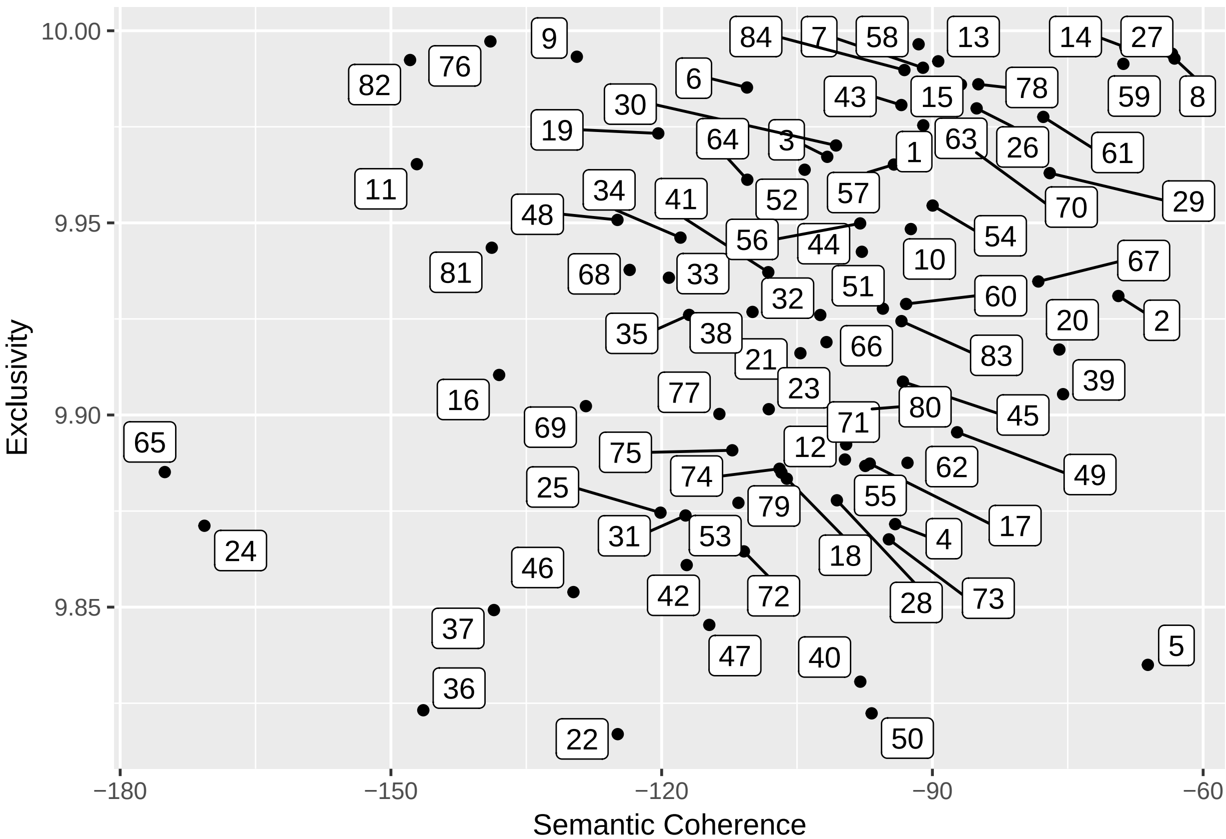


Figure 21: Coherence of k0 Topic Models

Table 19: Count and Distribution of Topics – k0

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

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

| Topic Number | AWS Speeches | Percent of AWS Speeches | Non-AWS Speeches | Percent of non-AWS Speeches | Male MP Speeches | Percent of Male MP Speeches |
|---|---|---|---|---|---|---|
| Topic 18 | 373 | 0.69% | 110 | 0.39% | 1,019 | 0.6% |
| Topic 19 | 5 | 0.01% | 2 | 0.01% | NA | NA% |
| Topic 20 | 848 | 1.58% | 469 | 1.68% | 1,402 | 0.83% |
| Topic 21 | 832 | 1.55% | 573 | 2.06% | 2,731 | 1.61% |
| Topic 22 | 611 | 1.14% | 283 | 1.02% | 1,462 | 0.86% |
| Topic 23 | 1,125 | 2.09% | 414 | 1.49% | 2,779 | 1.64% |
| Topic 24 | 687 | 1.28% | 236 | 0.85% | 1,522 | 0.9% |
| Topic 25 | 743 | 1.38% | 465 | 1.67% | 1,841 | 1.09% |
| Topic 26 | 462 | 0.86% | 144 | 0.52% | 2,383 | 1.41% |
| Topic 27 | 1,183 | 2.2% | 435 | 1.56% | 5,936 | 3.51% |
| Topic 28 | 876 | 1.63% | 254 | 0.91% | 1,986 | 1.17% |
| Topic 29 | 1,013 | 1.88% | 484 | 1.74% | 3,881 | 2.29% |
| Topic 30 | 523 | 0.97% | 275 | 0.99% | 1,860 | 1.1% |
| Topic 31 | 582 | 1.08% | 367 | 1.32% | 586 | 0.35% |
| Topic 32 | 460 | 0.86% | 639 | 2.29% | 2,648 | 1.56% |
| Topic 33 | 417 | 0.78% | 109 | 0.39% | 1,330 | 0.79% |
| Topic 34 | 61 | 0.11% | 31 | 0.11% | 25 | 0.01% |
| Topic 35 | 506 | 0.94% | 242 | 0.87% | 1,661 | 0.98% |
| Topic 36 | 490 | 0.91% | 272 | 0.98% | 1,303 | 0.77% |
| Topic 37 | 346 | 0.64% | 347 | 1.25% | 757 | 0.45% |
| Topic 38 | 915 | 1.7% | 279 | 1% | 4,973 | 2.94% |
| Topic 39 | 1,149 | 2.14% | 582 | 2.09% | 4,542 | 2.68% |
| Topic 40 | 974 | 1.81% | 780 | 2.8% | 4,241 | 2.5% |
| Topic 41 | 434 | 0.81% | 109 | 0.39% | 583 | 0.34% |
| Topic 42 | 884 | 1.64% | 331 | 1.19% | 4,092 | 2.42% |
| Topic 43 | 363 | 0.67% | 105 | 0.38% | 1,011 | 0.6% |
| Topic 44 | 452 | 0.84% | 316 | 1.13% | 1,521 | 0.9% |
| Topic 45 | 1,103 | 2.05% | 633 | 2.27% | 1,659 | 0.98% |
| Topic 46 | 756 | 1.41% | 285 | 1.02% | 3,008 | 1.78% |
| Topic 47 | 1,291 | 2.4% | 544 | 1.95% | 5,110 | 3.02% |
| Topic 48 | 514 | 0.96% | 129 | 0.46% | 1,020 | 0.6% |
| Topic 49 | 932 | 1.73% | 489 | 1.76% | 1,067 | 0.63% |
| Topic 50 | 848 | 1.58% | 592 | 2.12% | 2,617 | 1.55% |
| Topic 51 | 953 | 1.77% | 425 | 1.53% | 2,233 | 1.32% |
| Topic 52 | 275 | 0.51% | 161 | 0.58% | 834 | 0.49% |
| Topic 53 | 474 | 0.88% | 350 | 1.26% | 1,408 | 0.83% |
| Topic 54 | 774 | 1.44% | 363 | 1.3% | 4,264 | 2.52% |
| Topic 55 | 1,429 | 2.66% | 208 | 0.75% | 1,604 | 0.95% |
| Topic 56 | 263 | 0.49% | 438 | 1.57% | 1,597 | 0.94% |
| Topic 57 | 1,314 | 2.44% | 328 | 1.18% | 5,316 | 3.14% |
| Topic 58 | 40 | 0.07% | NA | NA% | 37 | 0.02% |
| Topic 59 | 113 | 0.21% | 88 | 0.32% | 474 | 0.28% |
| Topic 60 | 676 | 1.26% | 251 | 0.9% | 1,055 | 0.62% |
| Topic 61 | 555 | 1.03% | 351 | 1.26% | 2,610 | 1.54% |

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

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

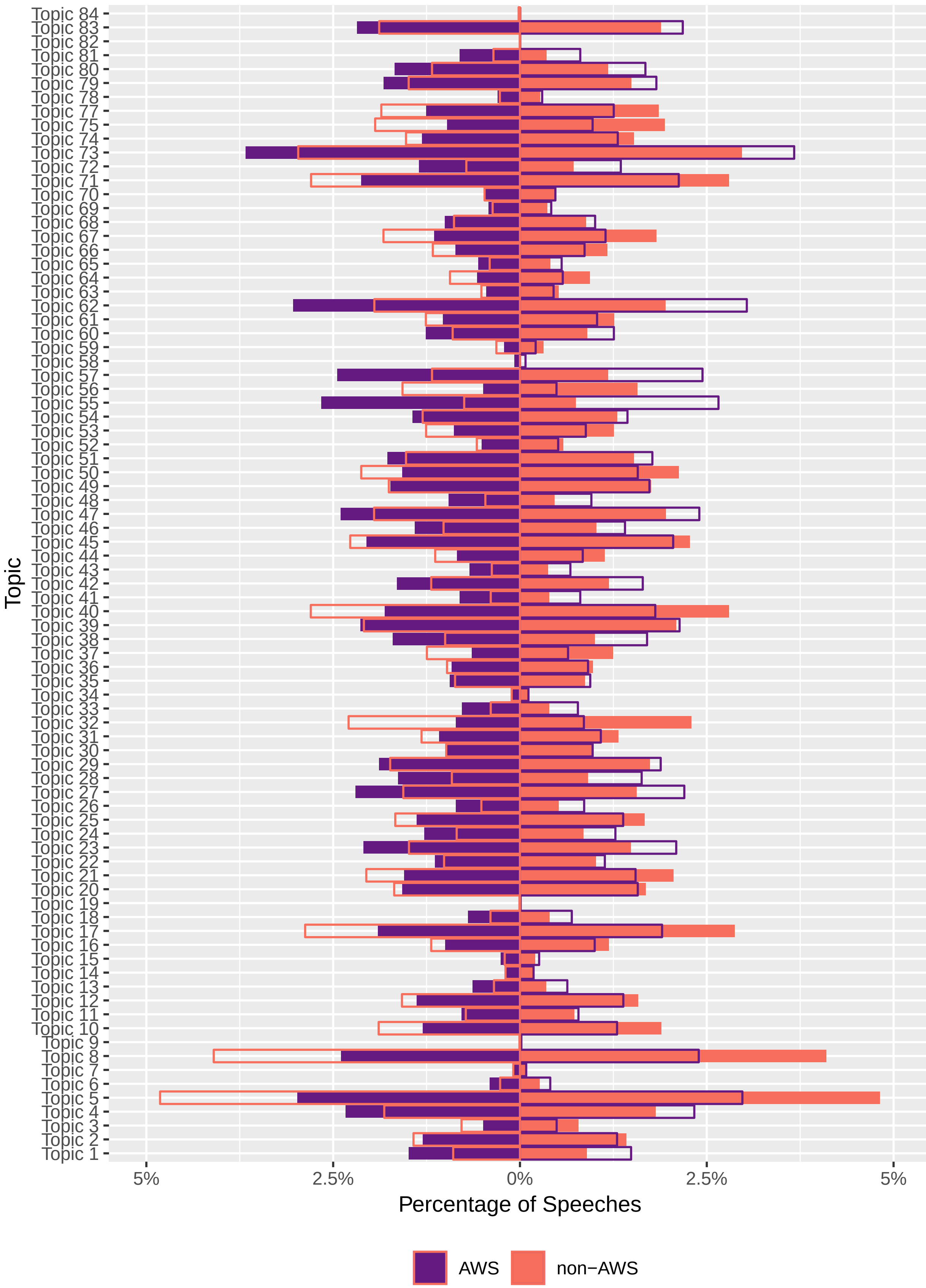


Figure 22: k0 Pyramid Chart

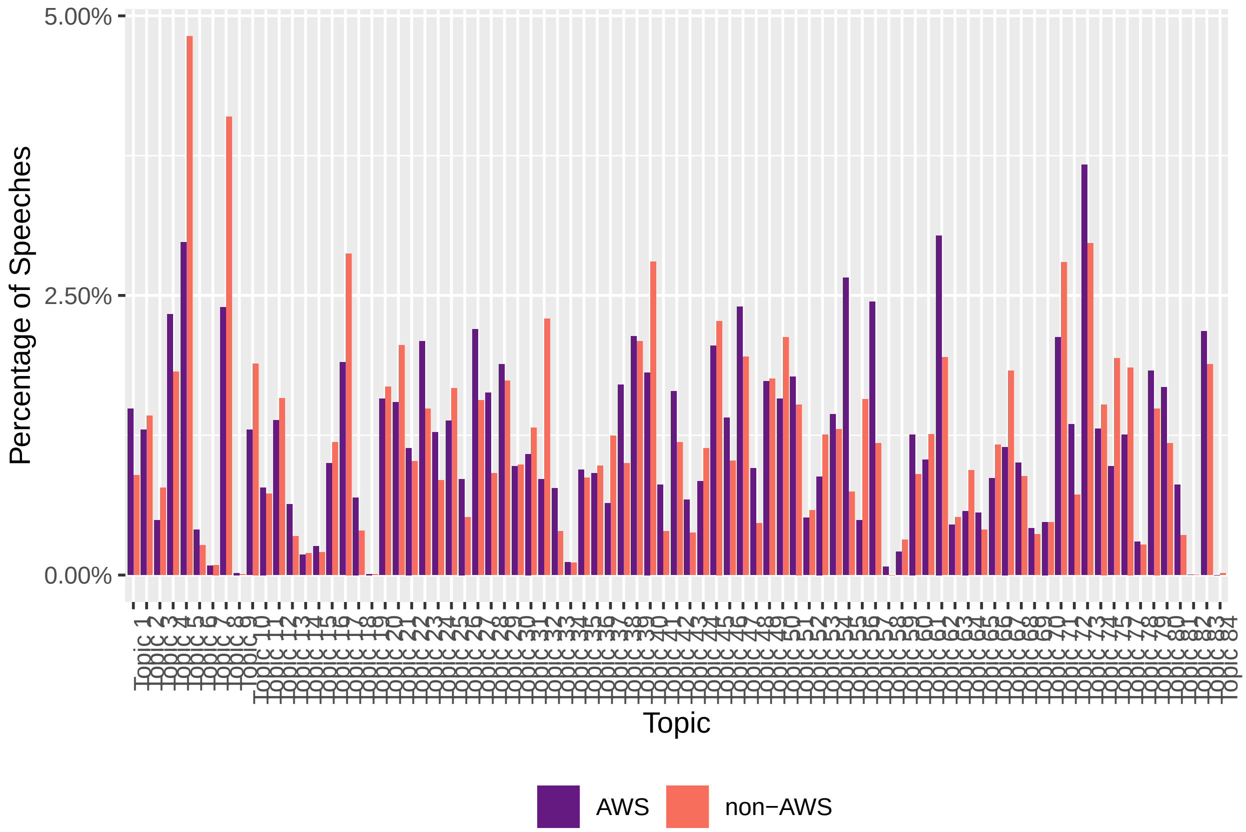


Figure 23: k0 Bar Chart

#### 4.4.1.1 Word Occurences

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

Table 20: Words in topic - k0

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

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

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

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

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

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

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

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

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

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

| Topic Number | Top Ten Words | Top Ten FREX |
|---|---|---|
| Topic 40 | international, countries, world, development, aid, developing, uk, country, trade, global, nations, africa, united, un, commonwealth, government, foreign, political, overseas, british | zimbabwe, burma, dfid, congo, burmese, sri, 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 20: Words in topic - k0 *(continued)*

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

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

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

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

| Topic Number | Top Ten Words | Top Ten FREX |
|---|---|---|
| Topic 67 | local, authorities, council, authority, councils, area, areas, government, communities, services, county, provision, needs, power, councillors, level, central, locally, powers, duty | local, authorities, councils, authority, councillors, council, county, unitary, locally, localism, council's, lancashire, authority's, parish, councillor, district, exeter, area, norwich, boards |
| Topic 68 | rights, wales, human, northern, ireland, commission, welsh, assembly, convention, act, equality, discrimination, commissioner, government, england, cardiff, duty, law, uk, respect | ireland, welsh, rights, assembly, wales, convention, human, northern, commissioner, cymru, discrimination, ehrc, commissions, echr, equality, assembly's, cardiff, strands, commission, belfast |
| Topic 69 | east, st, south, friends, heard, west, birmingham, leicester, north, eastmr, smith, sunderland, helier, brent, ealing, croydon, under-secretary, speeches, jones, called | helier, cooper, bromley, stuart, croydon, ealing, castlefordyvette, ewellchris, holborn, normanton, coventry, dobson, eastmr, hayes, brent, epsom, helens, mitcham, bury, stoke-on-trent |
| Topic 70 | member, members, debate, speech, also, spoke, mentioned, made, congratulate, talked, comments, north, remarks, raised, pointed, referred, said, follow, pleasure, excellent | member, spoke, remarks, talked, thoughtful, eloquently, pleasure, pointed, cambridgeshiremr, bermondsey, reminded, clarke, powerfully, norfolkmr, southwark, comments, passion, eloquent, congratulate, passionately |
| Topic 71 | european, eu, union, uk, europe, states, british, countries, negotiations, treaty, us, trade, agreement, united, britain, foreign, council, single, country, national | treaty, lisbon, european, eu, accession, brexit, euro, negotiations, enlargement, europe, gibraltar, negotiating, brussels, eurozone, sovereignty, directive, currency, treaties, meps, esm |
| Topic 72 | carers, family, constituent, told, families, life, home, caring, day, mother, many, man, lives, mrs, person, case, died, hours, week, can | carers, constituent, dementia, caring, mrs, husband, son, carer, daughter, mum, mother, wife, contacted, loved, father, respite, died, dad, sister, stories |
| Topic 73 | schools, education, school, teachers, students, university, children, pupils, skills, college, primary, teaching, higher, standards, system, universities, learning, colleges, training, free | schools, teachers, academies, grammar, fe, 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 20: Words in topic - k0 *(continued)*

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

```
## 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-inte
##       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
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##       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
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##      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:
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##       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
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## 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
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##       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)    0.0128866  0.0002383   54.07 <0.0000000000000002 ***
## short_listTRUE 0.0048994  0.0002873   17.05 <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)     0.0147977  0.0004181  35.393 < 0.0000000000000002 ***
## short_listTRUE -0.0018934  0.0005107  -3.707              0.00021 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0082626  0.0002465  33.520 < 0.0000000000000002 ***
## short_listTRUE -0.0012045  0.0003118  -3.863             0.000112 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0117235  0.0004650   25.21 < 0.0000000000000002 ***
## short_listTRUE 0.0030543  0.0005785    5.28           0.00000013 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 5:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0237338  0.0006279  37.796 <0.0000000000000002 ***
## short_listTRUE -0.0069940  0.0007739  -9.037 <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)    0.00869833 0.00009762  89.103 <0.0000000000000002 ***
## short_listTRUE 0.00023492 0.00012104   1.941             0.0523 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)     0.0152442  0.0001135  134.32 <0.0000000000000002 ***
## short_listTRUE -0.0019487  0.0001389  -14.03 <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)     0.0295306  0.0002215  133.29 <0.0000000000000002 ***
## short_listTRUE -0.0057599  0.0002625  -21.94 <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)    0.00668298 0.00006629  100.81 < 0.0000000000000002 ***
## short_listTRUE 0.00022484 0.00007570    2.97              0.00298 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)     0.0196173  0.0003437   57.08 <0.0000000000000002 ***
## short_listTRUE -0.0051479  0.0004241  -12.14 <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)    0.0055822  0.0002833  19.703 <0.0000000000000002 ***
## short_listTRUE 0.0006462  0.0003605   1.792             0.0731 .
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 12:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0110024  0.0003905  28.175 <0.0000000000000002 ***
## short_listTRUE 0.0001780  0.0004879   0.365               0.715
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0104919  0.0001332  78.782 <0.0000000000000002 ***
## short_listTRUE 0.0013421  0.0001603   8.374 <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)     0.01296710  0.00012743 101.757 <0.0000000000000002 ***
## short_listTRUE -0.00007168  0.00016019  -0.447               0.655
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##                Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0105005  0.0001064  98.660 < 0.0000000000000002 ***
## short_listTRUE 0.0010389  0.0001343   7.734   0.0000000000000105 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 16:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0091974  0.0003734  24.634 <0.0000000000000002 ***
## short_listTRUE 0.0002038  0.0004385   0.465               0.642
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
```

```
## Topic 17:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0154784  0.0004379  35.349 < 0.0000000000000002 ***
## short_listTRUE -0.0032849  0.0005570  -5.898         0.0000000037 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0079821  0.0002067   38.62 <0.0000000000000002 ***
## short_listTRUE 0.0036804  0.0002566   14.34 <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)     0.00579743  0.00007732  74.978 < 0.0000000000000002 ***
## short_listTRUE -0.00029399  0.00008299  -3.543             0.000396 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0137639  0.0003504  39.277 < 0.0000000000000002 ***
## short_listTRUE -0.0012426  0.0004266  -2.913              0.00358 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0149445  0.0004880  30.623 < 0.0000000000000002 ***
## short_listTRUE -0.0036329  0.0005957  -6.099        0.00000000107 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 22:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
```

```
## (Intercept)    0.0084289  0.0003501  24.077 <0.0000000000000002 ***
## short_listTRUE 0.0009436  0.0004333   2.178             0.0294 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 23:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0107244  0.0004882  21.968 < 0.0000000000000002 ***
## short_listTRUE 0.0029691  0.0005712   5.198          0.000000202 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0068247  0.0003519  19.391 < 0.0000000000000002 ***
## short_listTRUE 0.0031717  0.0004609   6.881     0.00000000000597 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 25:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0124805  0.0004100  30.441 < 0.0000000000000002 ***
## short_listTRUE -0.0019784  0.0005182  -3.818             0.000135 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0171470  0.0001834   93.52 <0.0000000000000002 ***
## short_listTRUE 0.0025460  0.0002271   11.21 <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)    0.0237729  0.0001806 131.611 < 0.0000000000000002 ***
## short_listTRUE 0.0013265  0.0002286   5.804        0.00000000651 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
##
## Topic 28:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0091601  0.0003763   24.34 <0.0000000000000002 ***
## short_listTRUE 0.0039083  0.0004726    8.27 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0185882  0.0003330  55.823 <0.0000000000000002 ***
## short_listTRUE -0.0001840  0.0003993  -0.461               0.645
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 30:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0162163  0.0002563  63.263 <0.0000000000000002 ***
## short_listTRUE 0.0007048  0.0002996   2.352              0.0187 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 31:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0097947  0.0003448  28.407 < 0.0000000000000002 ***
## short_listTRUE -0.0012487  0.0004212  -2.965              0.00303 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 32:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0175178  0.0004048   43.28 <0.0000000000000002 ***
## short_listTRUE -0.0075585  0.0004433  -17.05 <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)    0.0048027  0.0002604  18.445 < 0.0000000000000002 ***
## short_listTRUE 0.0022723  0.0003197   7.108     0.00000000000119 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 34:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0052889  0.0000903  58.574 <0.0000000000000002 ***
## short_listTRUE -0.0001472  0.0001101  -1.337               0.181
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 35:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0083614  0.0003079  27.154 <0.0000000000000002 ***
## short_listTRUE 0.0001052  0.0003918   0.269               0.788
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 36:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0078636  0.0003005  26.172 <0.0000000000000002 ***
## short_listTRUE 0.0003419  0.0003898   0.877                0.38
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 37:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0102526  0.0003854  26.600 < 0.0000000000000002 ***
## short_listTRUE -0.0034016  0.0004524  -7.519   0.0000000000000556 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 38:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0098010  0.0003749  26.141 < 0.0000000000000002 ***
## short_listTRUE 0.0030272  0.0004438   6.822     0.00000000000907 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 39:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0148555  0.0003749   39.62 <0.0000000000000002 ***
## short_listTRUE 0.0010571  0.0004556    2.32              0.0203 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 40:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0171985  0.0004972  34.587 < 0.0000000000000002 ***
## short_listTRUE -0.0045000  0.0005680  -7.923  0.00000000000000235 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 41:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0068644  0.0002438  28.152 < 0.0000000000000002 ***
## short_listTRUE 0.0018094  0.0003187   5.678         0.0000000137 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 42:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0086580  0.0004195   20.64 < 0.0000000000000002 ***
## short_listTRUE 0.0027449  0.0005288    5.19           0.00000021 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 43:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0137459  0.0001719   79.99 <0.0000000000000002 ***
## short_listTRUE 0.0034638  0.0002274   15.23 <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)     0.0148569  0.0002959  50.211 < 0.0000000000000002 ***
## short_listTRUE -0.0022506  0.0003127  -7.197    0.000000000000621 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 45:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0141120  0.0004696  30.053 < 0.0000000000000002 ***
## short_listTRUE -0.0019698  0.0005719  -3.444             0.000574 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 46:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0081217  0.0003795  21.401 < 0.0000000000000002 ***
## short_listTRUE 0.0024989  0.0005122   4.878           0.00000107 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 47:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0137948  0.0005357   25.75 < 0.0000000000000002 ***
## short_listTRUE 0.0023404  0.0006430    3.64             0.000273 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 48:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0068273  0.0002321   29.42 <0.0000000000000002 ***
## short_listTRUE 0.0044987  0.0003268   13.77 <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)    0.0128959  0.0003709  34.766 <0.0000000000000002 ***
## short_listTRUE 0.0006861  0.0004760   1.441                0.15
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 50:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0134293  0.0004220   31.82 < 0.0000000000000002 ***
## short_listTRUE -0.0026492  0.0004852   -5.46         0.0000000478 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 51:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0115991  0.0003944  29.408 < 0.0000000000000002 ***
## short_listTRUE 0.0015280  0.0005006   3.052              0.00227 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 52:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0121914  0.0002058  59.239 <0.0000000000000002 ***
## short_listTRUE -0.0021449  0.0002416  -8.878 <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)     0.0107990  0.0003205  33.694 < 0.0000000000000002 ***
## short_listTRUE -0.0027912  0.0003878  -7.197    0.000000000000619 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 54:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0153586  0.0002342  65.591 <0.0000000000000002 ***
## short_listTRUE 0.0003747  0.0002864   1.308               0.191
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
##
## Topic 55:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0081883  0.0003603   22.73 <0.0000000000000002 ***
## short_listTRUE 0.0089419  0.0004592   19.47 <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)     0.0171032  0.0002387   71.65 <0.0000000000000002 ***
## short_listTRUE -0.0060454  0.0002979  -20.30 <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)    0.0134712  0.0002541   53.01 <0.0000000000000002 ***
## short_listTRUE 0.0045580  0.0003278   13.90 <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)    0.00871704 0.00006437  135.41 <0.0000000000000002 ***
## short_listTRUE 0.00103234 0.00008269   12.48 <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)     0.0189661  0.0001353  140.15 <0.0000000000000002 ***
## short_listTRUE -0.0038754  0.0001691  -22.92 <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)    0.011130   0.000321  34.667 < 0.0000000000000002 ***
## short_listTRUE 0.002174   0.000424   5.128          0.000000294 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 61:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0153744  0.0002706  56.823 < 0.0000000000000002 ***
## short_listTRUE -0.0013718  0.0003493  -3.928            0.0000859 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 62:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0140840  0.0004659  30.231 <0.0000000000000002 ***
## short_listTRUE 0.0059448  0.0006486   9.166 <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)     0.01290593  0.00016940  76.186 <0.0000000000000002 ***
## short_listTRUE -0.00009548  0.00020619  -0.463               0.643
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 64:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0146860  0.0002487   59.06 <0.0000000000000002 ***
## short_listTRUE -0.0035600  0.0002896  -12.29 <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)    0.0051104  0.0002204  23.189 <0.0000000000000002 ***
## short_listTRUE 0.0005220  0.0002699   1.934              0.0531 .
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 66:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0095135  0.0003502  27.164 < 0.0000000000000002 ***
## short_listTRUE -0.0022132  0.0004272  -5.181          0.000000221 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 67:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0157397  0.0002885   54.56 <0.0000000000000002 ***
## short_listTRUE -0.0038345  0.0003586  -10.69 <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)    0.0079524  0.0002819  28.205 < 0.0000000000000002 ***
## short_listTRUE 0.0013677  0.0003486   3.923            0.0000876 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 69:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0051642  0.0002140  24.135 < 0.0000000000000002 ***
## short_listTRUE 0.0017690  0.0002854   6.198       0.000000000574 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 70:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0103966  0.0001825   56.96 <0.0000000000000002 ***
## short_listTRUE 0.0002397  0.0002261    1.06               0.289
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
```

```
## Topic 71:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0171814  0.0004688  36.652 < 0.0000000000000002 ***
## short_listTRUE -0.0033350  0.0005519  -6.042        0.00000000152 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 72:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0084307  0.0003818   22.08 <0.0000000000000002 ***
## short_listTRUE 0.0050625  0.0004652   10.88 <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)    0.0166756  0.0005216  31.971 < 0.0000000000000002 ***
## short_listTRUE 0.0031402  0.0006395   4.911           0.00000091 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 74:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0121470  0.0003729  32.575 < 0.0000000000000002 ***
## short_listTRUE -0.0012734  0.0004726  -2.694              0.00705 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 75:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0161789  0.0003983   40.62 <0.0000000000000002 ***
## short_listTRUE -0.0059030  0.0004610  -12.80 <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)     0.00394192  0.00003248  121.38 <0.0000000000000002 ***
## short_listTRUE -0.00054643  0.00003867  -14.13 <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)     0.0140380  0.0003407   41.20 <0.0000000000000002 ***
## short_listTRUE -0.0037164  0.0004009   -9.27 <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  0.0001145 102.415 <0.0000000000000002 ***
## short_listTRUE -0.0011789  0.0001399  -8.426 <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)    0.0128040  0.0004354  29.410 <0.0000000000000002 ***
## short_listTRUE 0.0009727  0.0005207   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)    0.0136203  0.0003367  40.451 < 0.0000000000000002 ***
## short_listTRUE 0.0015595  0.0004256   3.664             0.000248 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 81:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0035190  0.0002146   16.40 <0.0000000000000002 ***
## short_listTRUE 0.0030898  0.0002586   11.95 <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)    0.00308541 0.00002993 103.100 < 0.0000000000000002 ***
## short_listTRUE 0.00009994 0.00003668   2.725              0.00643 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 83:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0147526  0.0003403   43.35 <0.0000000000000002 ***
## short_listTRUE 0.0009714  0.0004518    2.15              0.0316 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 84:
##
## Coefficients:
##                   Estimate  Std. Error t value            Pr(>|t|)
## (Intercept)    0.002166039 0.000020726 104.509 <0.0000000000000002 ***
## short_listTRUE 0.000002153 0.000023569   0.091               0.927
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## 4.5 AWS References to Constituents in Context

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

Table 21: A random sample of KWIC's

| Pre | Keyword | Post |
|---|---|---|
| . I was briefed by a vehicle hire company in | my constituency | called Reflex and , quite frankly , 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 21: A random sample of KWIC's *(continued)*

| Pre | Keyword | Post |
|---|---|---|
| to use their abilities and develop their talents . In | my constituency | , 366 young people who have been unemployed for more |
| I believe that the most effective electoral registration officer in | my constituency | is mum . It is mum who fills in the |
| can arise from defective gas appliances , because two of | my constituents | , young students in their 20s , died from carbon |
| £ 3.6 million . Some 9 % of people in | my constituency | are hard-working , entrepreneurial self-employed people , and today is |
| my right hon . Friend congratulate 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 21: A random sample of KWIC's *(continued)*

| Pre | Keyword | Post |
|---|---|---|
| , but that does not help the large number of | my constituents | who have lost some , if not all , of |
| was the only mainstream candidate in the general election in | my constituency | who did not have their picture taken while pointing to |
| was not even in the mortgage application , NatWest told | my constituents | that it was in the process of adding it . |
| is a measure of the Government's achievement that people in | my constituency | and elsewhere in Northamptonshire can look forward to a secure |
| clothing company announced the closure of two more factories in | my constituency | and the neighbouring Erewash constituency . A huge number of |
| my primary care trust in 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 21: A random sample of KWIC's *(continued)*

| Pre | Keyword | Post |
|---|---|---|
| in child benefit , which will help 13,800 families in | my constituency | . My real reason for tabling the question is to |
| for Finchley and Golders GreenMike Freer ) , many of | my constituents | killed by lorries have died at junctions , including some |
| Hall the plight of former United Engineering Forgings workers in | my constituency | who will not receive the returns from their final salary |
| London has had Oyster cards for nine years , but | my constituents | are still waiting . Although Transport for Greater 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 21: A random sample of KWIC's *(continued)*

| Pre | Keyword | Post |
|---|---|---|
| about their corporate social responsibilities . For the sake of | my constituents | in Mitcham , Morden and Colliers Wood who want something |
| change in the law . Regrettably , 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 21: 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 21: 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 21: A random sample of KWIC's *(continued)*

| Pre | Keyword | Post |
|---|---|---|
| transparency about the impact . \ n " , " | My constituents | are also anxious about the Government's proposals to allow fracking |
| some of its provisions will have on vulnerable people in | my constituency | . \ n " , " I shall first raise |
| key elements of creative business growth . Creative businesses in | my constituency | and in a large area to the west of London |
| In Pembrokeshire we have two oil refineries , one in | my constituency | . They were both affected by the blockades in September |
| thank the Minister for his reply . 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 21: A random sample of KWIC's *(continued)*

| Pre | Keyword | Post |
|---|---|---|
| of those issues . \ n " , " In | my constituency | , the credit union benefits from capital and revenue from |
| children . I am indebted to a law company in | my constituency | called Just for Kids Law , which has raised with |
| hope they are not giving false hope to many of | my constituents | . Will they just admit that they have made a |
| I have a range of energy-intensive industries in | my constituency | , including steel , glass , paper and the entire |
| the save Lewisham hospital 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 21: A random sample of KWIC's *(continued)*

| Pre | Keyword | Post |
|---|---|---|
| to address have been influenced by what has happened in | my constituency | in the past 10 days as a series of incidents |
| , including those of Allied Steel and Wire's pensioners in | my constituency | ? They took the case to court through the unions |
| Indeed , it is a stealth cut . In | my constituency | , the Tories will have to make stealth cuts such |
| communities across the UK . I understand the concerns of | my constituents | . I understand that when a family from a different |
| a vested interest in ensuring the safety and security of | my constituency | , which in the past has been a military target |
| infrastructure project is a 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 21: 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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