All Women Short lists Methodology

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### 0.0.1 Descriptive Statistics

Labour MPs and Intakes

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| General Election | Total MPs | Labour MPs | Female Labour MPs | Labour MPs Intake | Intake Women | Intake Short list | Nominated Short list |
| 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 |

Data in this table is from House of Commons library reports (Audickas, Hawkins, & Cracknell, [2017](#ref-audickas2017); Kelly, [2016](#ref-kelly2016)). All women short lists were not used by Labour during the 2001 General Election.

Number of Speeches and Words in Dataset

Gender

Speeches

Words

All

656412

111180398

Female

148702

26231034

Male

507710

84949364

**Conservatives**

All

285291

44800169

Female

48768

7363031

Male

236523

37437138

**Labour**

All

261942

46494850

Female

84569

15897929

Non-All Women Shortlists

28695

5422776

All Women Shortlists

55874

10475153

Male

177373

30596921

**Liberal Democrat**

All

72716

13485902

Female

7552

1503459

Male

65164

11982443

**Other**

All

36463

6399477

Female

7813

1466615

Male

28650

4932862

# 1 Methodology

Previous research on gender differences in political speech patterns has focused on differences between male and female politicians (Yu, [2014](#ref-yu2014)) or on variations in Hilary Clinton’s speech patterns (Bligh, Merolla, Schroedel, & Gonzalez, [2010](#ref-bligh2010); Jones, [2016](#ref-jones2016)). 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 short lists. We examined differences in speaking styles using the Linguistic Inquiry and Word Count 2015 (LIWC) dictionary (Pennebaker, Boyd, Jordan, & Blackburn, [2015](#ref-pennebaker2015)) and the spaCy (Honnibal & Montani, [2017](#ref-honnibal2017)) 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 short lists to women who were not (but who theoretically had the opportunity to contest all-women short lists), 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](#fn1) Speeches and data on MPs’ gender and party affiliation are from a previously assembled dataset (Odell, [2018](#ref-odell2018)). Information on candidates selected through all women short lists is from the House of Commons Library (Kelly, [2016](#ref-kelly2016)). Unsuccessful General Election candidates selected through all women short lists who were subsequently elected in a byelection are classified as having been selected on an all women short list.

## 1.1 Linguistic Inquiry and Word Coun

Word classification used the Linguistic Inquiry and Word Count 2015 (LIWC) dictionary (Pennebaker et al., [2015](#ref-pennebaker2015)) and tokenising tools from the Quanteda R package (Benoit, [2018](#ref-benoit2018)). Word counts and words-per-sentence were calculated using stringi (Gagolewski, [2018](#ref-gagolewski2018)), a wrapper to the ICU regex library.

Following Yu ([2014](#ref-yu2014)) drawing on Newman, Groom, Handelman, & Pennebaker ([2008](#ref-newman2008)) we used 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)
* 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](#ref-kincaid1975)), calculated using Quanteda (Benoit, [2018](#ref-benoit2018)) and stringi (Gagolewski, [2018](#ref-gagolewski2018)).

## 1.2 Women vs Men

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

0.97

1.42

0.99

1.51

0.01

negligible

Verbs

12.82

5.00

12.67

5.36

-0.03

negligible

Auxiliary verbs

7.91

3.45

7.93

3.69

0.01

negligible

Social processes

8.47

4.82

8.18

5.11

-0.06

negligible

Positive emotions

2.73

2.49

2.57

2.54

-0.06

negligible

Negative emotions

1.15

1.68

1.07

1.77

-0.05

negligible

Tentative words

1.48

1.74

1.58

1.90

0.05

negligible

More than six letters

10.58

3.68

10.22

3.92

-0.10

negligible

Articles

7.65

3.30

7.96

3.55

0.09

negligible

Prepositions

12.58

4.42

12.14

4.73

-0.10

negligible

Anger words

0.23

0.81

0.24

0.77

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

43.63

19.68

41.15

20.04

-0.13

negligible

Total Word Count

402.79

691.27

370.18

647.36

-0.05

negligible

Flesh-Kincaid Grade Level

10.81

7.68

9.78

7.87

-0.13

negligible

There are no categories where gender differences meet the effect size threshold of \(|0.2|\) suggested by Cohen ([1988](#ref-cohen1988), 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](#ref-newman2008)).

## 1.3 Short lists vs Non-Short lists

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.

![\label{sl-key-variables}Occurence of selected LIWC terms](data:image/png;base64;base64,)

Occurence of selected LIWC terms

Effect Sizes for Female Labour MPs by selection process

All Women Short lists

Open Shorlists

Effect Size

Mean

SD

Mean

SD

Cohen’s D

Magnitude

All Pronouns

10.01

4.67

10.19

4.48

-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

8.48

4.94

8.46

4.59

0.00

negligible

Positive emotions

2.69

2.52

2.81

2.42

-0.05

negligible

Negative emotions

1.16

1.69

1.13

1.67

0.02

negligible

Tentative words

1.48

1.75

1.49

1.73

0.00

negligible

More than six letters

10.52

3.73

10.70

3.58

-0.05

negligible

Articles

7.69

3.38

7.55

3.15

0.04

negligible

Prepositions

12.55

4.54

12.63

4.15

-0.02

negligible

Anger words

0.23

0.78

0.24

0.88

-0.01

negligible

Swear words

0.00

0.06

0.00

0.05

0.01

negligible

Cognitive processes

8.59

4.90

8.86

4.69

-0.06

negligible

Words per Sentence

44.02

20.45

42.85

18.05

0.06

negligible

Total Word Count

401.77

704.40

404.78

664.97

0.00

negligible

Flesh-Kincaid Grade Level

10.97

7.97

10.48

7.06

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 \(|0.1|\).

## 1.4 Conservatives vs Labour

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

10.62

4.84

0.10

negligible

First person singular pronouns

1.98

2.51

2.15

2.56

0.07

negligible

First person plural pronouns

0.98

1.48

1.22

1.70

0.15

negligible

Verbs

12.72

5.24

12.93

5.13

0.04

negligible

Auxiliary verbs

7.92

3.61

8.17

3.58

0.07

negligible

Social processes

8.28

5.02

8.13

4.80

-0.03

negligible

Positive emotions

2.62

2.53

2.85

2.66

0.09

negligible

Negative emotions

1.10

1.74

1.05

1.78

-0.03

negligible

Tentative words

1.55

1.85

1.57

1.88

0.01

negligible

More than six letters

10.34

3.85

10.28

3.76

-0.02

negligible

Articles

7.86

3.48

7.82

3.45

-0.01

negligible

Prepositions

12.28

4.64

12.38

4.49

0.02

negligible

Anger words

0.24

0.78

0.24

0.82

0.01

negligible

Swear words

0.00

0.08

0.00

0.10

0.00

negligible

Cognitive processes

8.77

5.05

8.86

5.06

0.02

negligible

Words per Sentence

41.95

19.96

42.76

20.16

0.04

negligible

Total Word Count

380.71

662.03

335.54

592.41

-0.07

negligible

Flesh-Kincaid Grade Level

10.12

7.82

10.41

7.91

0.04

negligible

There are no categories with effect sizes exceeding \(|0.2|\) between Labour and Conservative MPs, like inter-Labour differences.

## 1.5 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](#ref-newman2008)).

Effect Sizes for Male and Female MPs, All Parties

Women

Men

Effect Size

Mean

SD

Mean

SD

Cohen’s D

Magnitude

All Pronouns

10.31

4.65

10.26

4.90

-0.01

negligible

First person singular pronouns

1.99

2.45

2.00

2.52

0.00

negligible

First person plural pronouns

1.11

1.57

1.08

1.59

-0.02

negligible

Verbs

12.88

4.97

12.80

5.26

-0.02

negligible

Auxiliary verbs

8.00

3.45

8.08

3.64

0.02

negligible

Social processes

8.45

4.77

8.00

4.93

-0.09

negligible

Positive emotions

2.84

2.53

2.69

2.58

-0.06

negligible

Negative emotions

1.10

1.65

1.08

1.78

-0.01

negligible

Tentative words

1.47

1.73

1.61

1.91

0.08

negligible

More than six letters

19.73

6.94

19.25

7.18

-0.07

negligible

Articles

7.62

3.31

8.00

3.51

0.11

negligible

Prepositions

12.58

4.36

12.22

4.62

-0.08

negligible

Anger words

0.23

0.78

0.25

0.82

0.02

negligible

Swear words

0.00

0.05

0.00

0.10

0.01

negligible

Cognitive processes

8.67

4.79

8.93

5.12

0.05

negligible

Words per Sentence

43.25

19.45

42.06

20.12

-0.06

negligible

Total Word Count

377.31

648.92

358.13

623.49

-0.03

negligible

Flesh-Kincaid Grade Level

10.63

7.61

10.16

7.89

-0.06

negligible

## 1.6 POS Analysis

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

22.18

9.60

21.66

10.96

-0.05

negligible

Plural Nouns

5.85

3.72

5.03

3.79

-0.22

small

Singular Nouns

15.62

9.84

16.01

11.19

0.04

negligible

Adjectives

9.58

4.78

9.28

5.29

-0.06

negligible

Adverbs

4.91

4.26

5.07

4.91

0.03

negligible

Verbs

20.94

9.52

20.78

10.28

-0.02

negligible

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

All Women Short lists

Open Shorlists

Effect Size

Word Type

Mean

SD

Mean

SD

Cohen’s D

Magnitude

All Nouns

22.16

8.78

22.18

10.00

-0.04

negligible

Plural Nouns

6.03

3.60

5.76

3.77

-0.16

negligible

Singular Nouns

15.51

8.97

15.67

10.26

0.02

negligible

Adjectives

9.83

4.59

9.45

4.86

-0.02

negligible

Adverbs

4.95

3.78

4.89

4.49

0.03

negligible

Verbs

20.88

9.04

20.97

9.76

-0.02

negligible

Part-of-speech (POS) tagging was done using spaCy (Honnibal & Montani, [2017](#ref-honnibal2017)) and the spacyr package (Benoit & Matsuo, [2018](#ref-benoit2018a)). There is one small gender difference (*d* = \(|0.22|\)) in the use of plural nouns, which make up 5.85% of the words used by female Labour MPs, compared to 5.03% 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.

## 1.7 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-short list women.

### 1.7.1 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.

![\label{gender-keyness}Keyness between Labour MPs, by Gender](data:image/png;base64;base64,)

Keyness between Labour MPs, by Gender

### 1.7.2 Short lists vs Non-Short lists

Keyness differences by selection process are not as obviously stereotypical. Nonetheless, the most common words amongst AWS MPs included “carers”, “disabled”, “bedroom” and “sen”[2](#fn2). 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.

![\label{sl-keyness}Keyness between Female Labour MPs, by Selection Process](data:image/png;base64;base64,)

Keyness between Female Labour MPs, by Selection Process

### 1.7.3 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.

![\label{party-keyness}Keyness between Labour and Conservative MPs](data:image/png;base64;base64,)

Keyness between Labour and Conservative MPs

## 1.8 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.

![\label{bigrams-keyness}Bigram Keyness in Female Labour MPs by Selection Process](data:image/png;base64;base64,)

Bigram Keyness in Female Labour MPs by Selection Process

## 1.9 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, 70.55% accuracy when predicting gender and 70.84% when predicting short lists. By contrast, the classifier could distinguish between Labour and Conservative speeches with 74.23% accuracy.

## 1.10 Topic Models

Using topic models to classify text is widely used in social sciences (Grimmer & Stewart, [2013](#ref-grimmer2013)), 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](#ref-grimmer2013)). 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](#ref-grimmer2013)) also highlight the importance of validating unsurpervised topic models when applied to new sets of texts.

The R package stm (Roberts, Stewart, & Tingley, [2018](#ref-roberts2018)) implements a structured topic model (STM) (Arora et al., [2013](#ref-arora2013); Roberts, Stewart, & Airoldi, [2016](#ref-roberts2016)). 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](#ref-blei2003)), 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.

We produced two different structured topic model implementations, with different numbers of topics (K). For each implementation, we created Fruchterman-Reingold (Fruchterman & Reingold, [1991](#ref-fruchterman1991)) diagrams. 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 of two topics.

### 1.10.1 Short lists vs Non-Short lists - K69

The first implementation used an algorithm developed by Lee & Mimno ([2014](#ref-lee2014c)), implemented in the stm package (Roberts et al., [2018](#ref-roberts2018)), to estimate the number of topics across all speeches made by female Labour MPs, using the “spectral” method developed by Arora et al. ([2013](#ref-arora2013)), implemented by Roberts et al. ([2018](#ref-roberts2018)). The resulting topic model has 69 topics, across 81,607 documents and a dictionary of 115,477 words. However, the topic quality with K = 69 is poor, and several topics have poor semantic coherence (see ).

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

![\label{k69-network}Fruchterman-Reingold plot of K69 Network](data:image/png;base64;base64,)

Fruchterman-Reingold plot of K69 Network

![\label{k69-coherence}Coherence of K69 Topic Models](data:image/png;base64;base64,)

Coherence of K69 Topic Models

Count and Distribution of Topics – K69

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| 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 | 1,272 | 2.37% | 353 | 1.27% | 3,434 | 2.03% |
| Topic 2 | 334 | 0.62% | 127 | 0.46% | 1,091 | 0.64% |
| Topic 3 | 241 | 0.45% | 71 | 0.25% | 427 | 0.25% |
| Topic 4 | 550 | 1.02% | 133 | 0.48% | 835 | 0.49% |
| Topic 5 | 826 | 1.54% | 206 | 0.74% | 2,452 | 1.45% |
| Topic 6 | 978 | 1.82% | 915 | 3.28% | 4,060 | 2.4% |
| Topic 7 | 648 | 1.21% | 236 | 0.85% | 1,770 | 1.05% |
| Topic 8 | 70 | 0.13% | 25 | 0.09% | 125 | 0.07% |
| Topic 9 | 265 | 0.49% | 309 | 1.11% | 862 | 0.51% |
| Topic 10 | 1,024 | 1.91% | 513 | 1.84% | 1,065 | 0.63% |
| Topic 11 | 940 | 1.75% | 580 | 2.08% | 3,793 | 2.24% |
| Topic 12 | 313 | 0.58% | 319 | 1.14% | 1,309 | 0.77% |
| Topic 13 | 325 | 0.61% | 146 | 0.52% | 1,181 | 0.7% |
| Topic 14 | 1,596 | 2.97% | 461 | 1.65% | 2,885 | 1.7% |
| Topic 15 | 1,386 | 2.58% | 642 | 2.3% | 4,686 | 2.77% |
| Topic 16 | 1,407 | 2.62% | 525 | 1.88% | 3,651 | 2.16% |
| Topic 17 | 3,690 | 6.87% | 1,459 | 5.23% | 19,359 | 11.43% |
| Topic 18 | 1,026 | 1.91% | 847 | 3.04% | 4,760 | 2.81% |
| Topic 19 | 640 | 1.19% | 423 | 1.52% | 2,130 | 1.26% |
| Topic 20 | 872 | 1.62% | 216 | 0.77% | 2,262 | 1.34% |
| Topic 21 | 658 | 1.23% | 363 | 1.3% | 914 | 0.54% |
| Topic 22 | 818 | 1.52% | 439 | 1.57% | 1,965 | 1.16% |
| Topic 23 | 795 | 1.48% | 518 | 1.86% | 3,553 | 2.1% |
| Topic 24 | 385 | 0.72% | 199 | 0.71% | 1,079 | 0.64% |
| Topic 25 | 240 | 0.45% | 74 | 0.27% | 422 | 0.25% |
| Topic 26 | 788 | 1.47% | 200 | 0.72% | 1,738 | 1.03% |
| Topic 27 | 266 | 0.5% | 120 | 0.43% | 1,010 | 0.6% |
| Topic 28 | 847 | 1.58% | 350 | 1.25% | 3,135 | 1.85% |
| Topic 29 | 1,110 | 2.07% | 327 | 1.17% | 944 | 0.56% |
| Topic 30 | 1,132 | 2.11% | 462 | 1.66% | 6,444 | 3.81% |
| Topic 31 | 996 | 1.85% | 975 | 3.49% | 6,077 | 3.59% |
| Topic 32 | 76 | 0.14% | 64 | 0.23% | 335 | 0.2% |
| Topic 33 | 1,238 | 2.31% | 985 | 3.53% | 6,613 | 3.9% |
| Topic 34 | 1,124 | 2.09% | 521 | 1.87% | 3,335 | 1.97% |
| Topic 35 | 650 | 1.21% | 657 | 2.35% | 2,294 | 1.35% |
| Topic 36 | 601 | 1.12% | 154 | 0.55% | 548 | 0.32% |
| Topic 37 | 455 | 0.85% | 194 | 0.7% | 1,554 | 0.92% |
| Topic 38 | 1,246 | 2.32% | 991 | 3.55% | 2,849 | 1.68% |
| Topic 39 | 1,917 | 3.57% | 936 | 3.35% | 7,664 | 4.53% |
| Topic 40 | 848 | 1.58% | 290 | 1.04% | 2,419 | 1.43% |
| Topic 41 | 63 | 0.12% | 40 | 0.14% | 204 | 0.12% |
| Topic 42 | 853 | 1.59% | 590 | 2.11% | 2,016 | 1.19% |
| Topic 43 | 1,344 | 2.5% | 604 | 2.16% | 2,266 | 1.34% |
| Topic 44 | 814 | 1.52% | 288 | 1.03% | 3,005 | 1.77% |
| Topic 45 | 602 | 1.12% | 474 | 1.7% | 1,086 | 0.64% |
| Topic 46 | 709 | 1.32% | 150 | 0.54% | 1,646 | 0.97% |
| Topic 47 | 664 | 1.24% | 245 | 0.88% | 2,992 | 1.77% |
| Topic 48 | 940 | 1.75% | 901 | 3.23% | 3,045 | 1.8% |
| Topic 49 | 835 | 1.55% | 563 | 2.02% | 2,537 | 1.5% |
| Topic 50 | 1,328 | 2.47% | 1,219 | 4.37% | 3,421 | 2.02% |
| Topic 51 | 1,076 | 2% | 323 | 1.16% | 2,453 | 1.45% |
| Topic 52 | 196 | 0.36% | 85 | 0.3% | 758 | 0.45% |
| Topic 53 | 590 | 1.1% | 293 | 1.05% | 746 | 0.44% |
| Topic 54 | 1,057 | 1.97% | 824 | 2.95% | 5,570 | 3.29% |
| Topic 55 | 302 | 0.56% | 157 | 0.56% | 868 | 0.51% |
| Topic 56 | 535 | 1% | 398 | 1.43% | 847 | 0.5% |
| Topic 57 | 656 | 1.22% | 314 | 1.13% | 1,990 | 1.18% |
| Topic 58 | 468 | 0.87% | 182 | 0.65% | 1,125 | 0.66% |
| Topic 59 | 426 | 0.79% | 183 | 0.66% | 700 | 0.41% |
| Topic 60 | 562 | 1.05% | 297 | 1.06% | 1,389 | 0.82% |
| Topic 61 | 86 | 0.16% | 28 | 0.1% | 174 | 0.1% |
| Topic 62 | 550 | 1.02% | 343 | 1.23% | 746 | 0.44% |
| Topic 63 | 690 | 1.28% | 252 | 0.9% | 1,726 | 1.02% |
| Topic 64 | 594 | 1.11% | 244 | 0.87% | 2,247 | 1.33% |
| Topic 65 | 662 | 1.23% | 457 | 1.64% | 907 | 0.54% |
| Topic 66 | 1,493 | 2.78% | 527 | 1.89% | 4,073 | 2.41% |
| Topic 67 | 737 | 1.37% | 451 | 1.62% | 3,237 | 1.91% |
| Topic 68 | 279 | 0.52% | 145 | 0.52% | 547 | 0.32% |
| Topic 69 | 1 | 0% | NA | NA% | NA | NA% |

![\label{k69-topic-pyramid-pllot}K69 Pyramid Chart](data:image/png;base64;base64,)

K69 Pyramid Chart

![\label{k69-topic-bar-plot}K69 Bar Chart](data:image/png;base64;base64,)

K69 Bar Chart

#### 1.10.1.1 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](#ref-airoldi2016)).

|  |  |  |
| --- | --- | --- |
| Topic Number | Top Ten Words | Top Ten FREX |
| Topic 1 | secretary, state, tell, ministers, given, today, department, can, confirm, said | secretary, state, confirm, tell, ministers, state’s, minister’s, explain, please, discussions |
| Topic 2 | safety, register, registration, indicated, registered, electoral, risk, risks, number, individual | registration, indicated, hse, canvass, register, gurkhas, safety, dissent, hare, trustee |
| Topic 3 | make, sure, statement, progress, difference, northern, ireland, towards, representations, responsibilities | statement, make, sure, progress, ireland, representations, difference, northern, milton, departmental |
| Topic 4 | debt, water, credit, charges, pay, loan, loans, people, financial, cost | payday, loan, lenders, debts, loans, debt, charges, water, high-cost, creditors |
| Topic 5 | house, committee, parliament, leader, select, motion, parliamentary, debate, scrutiny, business | select, leader, house, motion, committee, backbench, scrutiny, committees, benchers, parliamentary |
| Topic 6 | new, development, work, need, investment, strategy, must, programme, working, also | development, strategy, develop, project, regional, projects, partnership, together, developed, build |
| Topic 7 | road, petition, residents, car, vehicles, petitioners, dogs, roads, site, house | petitioners, lap-dancing, petition, dogs, dog, pedestrians, cycling, declares, drivers, accidents |
| Topic 8 | important, agree, welcome, country, making, particularly, thank, part, makes, good | agree, welcome, important, absolutely, makes, making, friend’s, thank, particularly, giving |
| Topic 9 | companies, market, company, competition, energy, consumers, prices, price, consumer, customers | competition, companies, market, wholesale, suppliers, company, regulator, ofgem, supplier, consumers |
| Topic 10 | women, men, equality, women’s, discrimination, rights, gender, equal, woman, marriage | gender, bishops, transgender, women’s, women, abortion, same-sex, marriage, equality, gay |
| Topic 11 | energy, climate, fuel, change, green, carbon, emissions, gas, environmental, industry | renewables, solar, insulation, feed-in, biofuels, greenhouse, dioxide, kyoto, carbon, climate |
| Topic 12 | office, post, offices, royal, service, closure, mail, services, network, christmas | offices, mail, sub-post, post, sub-postmasters, closures, consignia, swindon, closure, office |
| Topic 13 | mr, north, south, east, west, spoke, friends, birmingham, talked, central | ealing, spoke, dorset, lothian, ayrshire, glasgow, chris, southwark, pontefract, birmingham |
| Topic 14 | pension, scheme, benefit, pensions, benefits, pensioners, system, credit, allowance, income | pension, esa, pensions, claimants, retirement, pip, pensioners, incapacity, dwp, means-testing |
| Topic 15 | economy, jobs, economic, growth, unemployment, country, investment, chancellor, budget, crisis | unemployment, recession, growth, economy, obr, deficit, inflation, economic, forecast, borrowing |
| Topic 16 | schools, school, education, children, teachers, parents, pupils, educational, special, primary | academies, pupil, grammar, schools, pupils, teachers, ofsted, school, teacher, sen |
| Topic 17 | want, say, one, think, know, need, us, get, go, see | think, say, things, want, something, saying, going, lot, really, go |
| Topic 18 | review, report, commission, independent, process, recommendations, inquiry, also, system, standards | recommendations, inquiry, panel, audit, independent, recommendation, reviews, fsa, complaints, review |
| Topic 19 | business, businesses, small, financial, bank, banks, insurance, rates, industry, enterprise | smes, medium-sized, businesses, bank, enterprises, enterprise, banking, rbs, business, rock |
| Topic 20 | wales, industry, welsh, north-east, england, assembly, constituency, jobs, manufacturing, uk | welsh, wales, steel, cardiff, north-east, assembly, visteon, newcastle, manufacturing, tyneside |
| Topic 21 | care, services, social, mental, need, health, home, provision, service, older | mental, care, social, elderly, older, advocacy, services, residential, palliative, discharges |
| Topic 22 | pay, work, workers, employment, working, wage, minimum, employers, paid, national | wage, workers, zero-hours, employees, paternity, employer, minimum, employers, employment, workplace |
| Topic 23 | amendment, clause, amendments, new, 1, lords, section, 2, act, clauses | amendment, nos, insert, subsection, clause, amendments, clauses, section, lords, schedule |
| Topic 24 | report, last, since, said, received, published, year, following, official, end | march, vol, official, january, july, november, published, december, june, october |
| Topic 25 | made, clear, impact, decision, changes, recent, assessment, decisions, effect, proposed | made, decision, assessment, clear, decisions, impact, implications, recent, changes, effect |
| Topic 26 | funding, cuts, fund, cut, budget, grant, spending, bbc, review, flood | flood, funding, bbc, formula, grant, flooding, floods, cumbria, lottery, grants |
| Topic 27 | money, spent, extra, spend, liberal, cost, spending, value, opposition, tory | money, spent, liberal, spend, democrats, tories, tory, lib, democrat, conservatives |
| Topic 28 | constituency, great, community, proud, many, sport, one, also, world, new | maiden, arts, football, museum, museums, sport, olympic, games, sports, heritage |
| Topic 29 | families, child, poverty, children, parents, work, credit, working, family, living | lone, poverty, childcare, families, low-income, child, nursery, four-year-olds, nurseries, joseph |
| Topic 30 | party, conservative, vote, parliament, political, election, labour, parties, scottish, elected | party, vote, voting, conservative, party’s, voters, election, voted, votes, politics |
| Topic 31 | point, can, may, issue, take, however, whether, matter, understand, consider | matter, point, understand, consider, certainly, accept, possible, issue, course, happy |
| Topic 32 | member, said, lady, mentioned, raised, comments, speech, referred, points, remarks | member, lady, comments, remarks, bromley, interesting, chislehurst, pointed, front-bench, mentioned |
| Topic 33 | european, uk, eu, countries, united, union, europe, states, british, trade | accession, enlargement, wto, lisbon, treaty, eu, doha, european, negotiations, brexit |
| Topic 34 | education, skills, young, training, students, university, college, higher, science, apprenticeships | ema, fe, students, apprenticeship, universities, qualifications, apprenticeships, graduates, vocational, courses |
| Topic 35 | local, authorities, authority, planning, community, communities, councils, area, guidance, system | authorities, local, authority, planning, councils, councillors, locally, guidance, localism, communities |
| Topic 36 | disabled, carers, disability, support, disabilities, needs, caring, autism, learning, can | carers, autism, autistic, disabled, disabilities, disability, dementia, carer, caring, deaf |
| Topic 37 | environment, marine, fishing, sea, industry, natural, fish, countryside, rural, fisheries | fishermen, cod, forestry, biodiversity, habitats, mmo, fishing, fish, cfp, fisheries |
| Topic 38 | justice, court, violence, victims, cases, criminal, domestic, courts, prison, offence | attorney-general, defendants, defendant, prison, prosecutors, solicitor-general, stalking, prosecutor, prisons, prosecution |
| Topic 39 | international, foreign, rights, human, peace, un, conflict, world, aid, war | israel, palestinian, israeli, gaza, sri, zimbabwe, iran, yemen, hamas, palestinians |
| Topic 40 | day, family, never, told, families, life, happened, constituent, man, went | man, died, son, story, stories, hillsborough, tragedy, daughter, husband, angry |
| Topic 41 | proposals, future, forward, consultation, plans, meet, paper, current, discuss, bring | proposals, consultation, paper, plans, forward, discuss, white, proposal, meet, implement |
| Topic 42 | behaviour, crime, antisocial, alcohol, young, drugs, drug, problem, use, tackle | antisocial, asbos, alcohol, alcohol-related, binge, psychoactive, drinking, fireworks, behaviour, graffiti |
| Topic 43 | housing, homes, social, affordable, private, home, accommodation, rent, need, properties | housing, tenants, rented, tenancies, homelessness, leasehold, landlords, rents, properties, leaseholders |
| Topic 44 | question, order, mr, put, asked, answer, questions, ask, speaker, time | question, answer, questions, speaker, asked, deputy, answers, order, apologise, read |
| Topic 45 | research, cancer, treatment, medical, condition, screening, disease, can, patients, use | embryos, prostate, cervical, hepatitis, cloning, transplant, embryo, fertilisation, embryonic, endometriosis |
| Topic 46 | online, internet, farmers, animals, digital, animal, broadband, sites, tickets, technology | cull, badgers, badger, fur, bovine, mink, culling, circuses, touts, snares |
| Topic 47 | defence, forces, armed, plymouth, personnel, service, military, army, nuclear, royal | mod, naval, hms, submarines, dockyard, veterans, armed, plymouth, covenant, personnel |
| Topic 48 | information, home, security, data, immigration, control, orders, system, terrorism, appeal | extradition, tpims, sia, warrant, detention, checks, tpim, terrorism, intercept, identity |
| Topic 49 | police, officers, crime, policing, home, force, service, forces, officer, chief | constable, constables, officers, policing, police, soca, ipcc, constabulary, pcsos, hmic |
| Topic 50 | nhs, hospital, patients, health, services, hospitals, care, service, trust, trusts | dentists, dentistry, pharmacies, pct, nhs, hospitals, hospital, dental, trusts, patients |
| Topic 51 | tax, budget, cut, chancellor, cuts, rate, income, vat, benefit, hit | 50p, vat, millionaires, hit, tax, allowances, credits, richest, chancellor, ifs |
| Topic 52 | years, now, two, time, first, three, past, one, months, ago | years, three, months, ago, two, past, weeks, five, four, now |
| Topic 53 | staff, doctors, emergency, medical, service, training, nurses, royal, junior, ambulance | ambulance, junior, staffing, doctors, halifax, posts, nurses, fss, staff, cpr |
| Topic 54 | bill, legislation, act, law, rights, provisions, powers, regulations, place, believe | bill, legislation, bill’s, provisions, passage, regulations, legislative, draft, statute, definition |
| Topic 55 | public, sector, private, organisations, service, voluntary, services, society, community, organisation | public, voluntary, organisations, sector, private, co-operative, volunteering, volunteers, volunteer, co-operatives |
| Topic 56 | health, national, inequalities, programme, suicide, disease, department, prevention, among, risk | flu, hiv, pandemic, inequalities, infections, suicide, mortality, infection, mrsa, vaccine |
| Topic 57 | council, london, areas, city, area, constituency, centre, rural, county, liverpool | county, mayor, borough, cities, liverpool, city, regeneration, council’s, london, towns |
| Topic 58 | advice, legal, cases, civil, hull, aid, case, compensation, claims, service | hull, tribunal, legal, compensation, solicitors, advice, concentrix, servants, lawyers, tribunals |
| Topic 59 | people, work, many, young, get, people’s, can, help, lives, job | people, people’s, get, getting, work, young, jobcentre, lives, youth, find |
| Topic 60 | tax, revenue, relief, duty, uk, avoidance, hmrc, charities, companies, taxation | evasion, hmrc, gaar, avoidance, inland, stamp, revenue, relief, gift, dependencies |
| Topic 61 | government, government’s, policy, labour, previous, scotland, scottish, commitment, policies, coalition | government, previous, policy, government’s, scotland, coalition, scottish, labour, disappointing, administrations |
| Topic 62 | trafficking, home, uk, asylum, refugees, immigration, country, human, migration, britain | trafficking, slavery, trafficked, sierra, leone, slave, dubs, fgm, yarl’s, wilberforce |
| Topic 63 | food, products, industry, smoking, advertising, tobacco, ban, product, standards, shops | gambling, betting, sunbed, tobacco, cocoa, meat, supermarkets, labelling, retailers, packaging |
| Topic 64 | members, debate, many, issues, also, today, heard, opportunity, hope, issue | members, debate, heard, speak, sides, issues, hear, opportunity, listened, pleased |
| Topic 65 | children, child, parents, young, children’s, family, contact, vulnerable, adoption, abuse | csa, adopters, adoption, child’s, cafcass, looked-after, children’s, children, safeguarding, barred |
| Topic 66 | transport, rail, bus, services, line, travel, train, network, passengers, london | rail, passengers, passenger, heathrow, hs2, freight, high-speed, crossrail, airlines, runway |
| Topic 67 | year, million, number, increase, figures, increased, billion, 1, average, cost | million, figures, figure, increased, increase, compared, year, total, fallen, estimates |
| Topic 68 | support, ensure, can, help, aware, taking, take, provide, action, continue | aware, ensure, support, taking, steps, continue, help, action, assure, encourage |
| Topic 69 | deal, recently, new, can, lack, great, concern, done, move, given | deal, recently, lack, elsewhere, concern, great, improved, offered, done, new |

### 1.10.2 Short lists vs Non-Short lists - K30

As seen in the word lists above, there is relatively scattershot semantic coherence, although exclusivity is high, when using the 69 topic models suggested by Lee and Mimno’s ([2014](#ref-lee2014c)) algorithm. We therefore re-ran the analysis, using 30 topic models, which has resulted in increased semantic coherence, albeit with slightly lower exclusivity, as illustrated in Figure .

![\label{k30-network}Fruchterman-Reingold plot of K30 Network](data:image/png;base64;base64,)

Fruchterman-Reingold plot of K30 Network

![\label{k30-coherence}Coherence of K30 Topic Models](data:image/png;base64;base64,)

Coherence of K30 Topic Models

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 |
| Topic 1 | 1,792 | 3.34% | 1,229 | 4.4% | 8,163 | 4.82% |
| Topic 2 | 2,476 | 4.61% | 2,514 | 9.01% | 11,394 | 6.73% |
| Topic 3 | 1,082 | 2.01% | 632 | 2.27% | 926 | 0.55% |
| Topic 4 | 1,302 | 2.42% | 900 | 3.23% | 3,364 | 1.99% |
| Topic 5 | 1,976 | 3.68% | 1,371 | 4.91% | 9,653 | 5.7% |
| Topic 6 | 1,720 | 3.2% | 623 | 2.23% | 4,562 | 2.69% |
| Topic 7 | 2,721 | 5.07% | 758 | 2.72% | 4,045 | 2.39% |
| Topic 8 | 879 | 1.64% | 381 | 1.37% | 2,192 | 1.29% |
| Topic 9 | 1,008 | 1.88% | 743 | 2.66% | 1,747 | 1.03% |
| Topic 10 | 1,351 | 2.52% | 658 | 2.36% | 6,235 | 3.68% |
| Topic 11 | 2,144 | 3.99% | 1,552 | 5.56% | 4,494 | 2.65% |
| Topic 12 | 2,507 | 4.67% | 883 | 3.16% | 10,394 | 6.14% |
| Topic 13 | 1,231 | 2.29% | 825 | 2.96% | 3,971 | 2.34% |
| Topic 14 | 985 | 1.83% | 646 | 2.32% | 1,570 | 0.93% |
| Topic 15 | 1,180 | 2.2% | 1,410 | 5.05% | 4,935 | 2.91% |
| Topic 16 | 2,175 | 4.05% | 1,302 | 4.67% | 7,547 | 4.46% |
| Topic 17 | 5,309 | 9.89% | 2,357 | 8.45% | 25,255 | 14.91% |
| Topic 18 | 2,362 | 4.4% | 1,003 | 3.59% | 6,230 | 3.68% |
| Topic 19 | 1,183 | 2.2% | 445 | 1.59% | 3,305 | 1.95% |
| Topic 20 | 1,334 | 2.48% | 561 | 2.01% | 2,075 | 1.23% |
| Topic 21 | 4,361 | 8.12% | 1,556 | 5.58% | 11,845 | 6.99% |
| Topic 22 | 977 | 1.82% | 359 | 1.29% | 2,259 | 1.33% |
| Topic 23 | 1,787 | 3.33% | 890 | 3.19% | 6,124 | 3.62% |
| Topic 24 | 813 | 1.51% | 233 | 0.84% | 2,132 | 1.26% |
| Topic 25 | 1,604 | 2.99% | 1,104 | 3.96% | 4,917 | 2.9% |
| Topic 26 | 1,237 | 2.3% | 664 | 2.38% | 1,105 | 0.65% |
| Topic 27 | 668 | 1.24% | 325 | 1.16% | 1,796 | 1.06% |
| Topic 28 | 3,218 | 5.99% | 1,001 | 3.59% | 8,906 | 5.26% |
| Topic 29 | 1,121 | 2.09% | 304 | 1.09% | 4,463 | 2.64% |
| Topic 30 | 1,202 | 2.24% | 673 | 2.41% | 3,746 | 2.21% |

![\label{k30-topic-pyramid-plot}K30 Pyramid Chart](data:image/png;base64;base64,)

K30 Pyramid Chart

![\label{k30-topic-bar-plot}K30 Bar Chart](data:image/png;base64;base64,)

K30 Bar Chart

#### 1.10.2.1 Word Occurences

Words in topic

|  |  |  |
| --- | --- | --- |
| Topic Number | Top Ten Words | Top Ten FREX |
| Topic 1 | bill, amendment, clause, new, legislation, amendments, act, committee, provisions, 1 | amendment, clause, amendments, clauses, nos, insert, subsection, provisions, bill, tabled |
| Topic 2 | issues, public, information, also, report, review, process, work, need, important | consultation, review, guidance, recommendations, information, considering, decisions, arrangements, framework, detailed |
| Topic 3 | women, men, pay, equality, rights, women’s, discrimination, equal, work, woman | women, equality, gender, equalities, bishops, discrimination, female, women’s, equal, men |
| Topic 4 | police, crime, officers, behaviour, policing, home, antisocial, community, work, force | policing, antisocial, constable, burglary, wardens, crime, constabulary, police, officers, pcsos |
| Topic 5 | european, uk, countries, eu, union, trade, international, united, world, british | treaty, enlargement, wto, lisbon, doha, eu, eu’s, mod, multilateral, accession |
| Topic 6 | transport, london, rail, bus, road, services, line, travel, network, train | rail, bus, passengers, fares, trains, buses, passenger, heathrow, congestion, hs2 |
| Topic 7 | people, work, benefit, pension, benefits, support, disabled, employment, carers, working | disabled, jobcentre, incapacity, carers, pension, claimants, esa, dla, pensions, atos |
| Topic 8 | immigration, safety, uk, asylum, enforcement, home, number, illegal, licensing, animals | dogs, dog, id, visa, fur, mink, hse, sia, seekers, fireworks |
| Topic 9 | health, research, cancer, treatment, medical, disease, can, smoking, patients, people | cancer, diseases, vaccine, flu, embryos, infections, diabetes, palliative, prostate, cervical |
| Topic 10 | government, labour, conservative, party, opposition, policy, government’s, scotland, scottish, members | conservative, liberal, democrats, conservatives, scottish, democrat, scotland, tory, interruption, tories |
| Topic 11 | care, health, nhs, services, service, hospital, patients, staff, trust, social | dentists, ambulance, dentistry, helier, dentist, nurses, hospital, pct, hospitals, dental |
| Topic 12 | member, members, debate, house, mr, committee, said, time, speaker, north | member, speaker, mr, debate, spoke, thoughtful, backbench, debates, madam, select |
| Topic 13 | companies, financial, company, market, scheme, money, debt, consumers, bank, credit | payday, annuity, oft, policyholders, penrose, fca, loan, prepayment, loans, annuities |
| Topic 14 | young, people, health, mental, youth, prison, problems, drugs, alcohol, drug | prisons, probation, cannabis, reoffending, mental, prison, self-harm, youth, alcohol, sentences |
| Topic 15 | cases, court, legal, law, case, justice, evidence, criminal, courts, home | judicial, attorney-general, defendant, extradition, tpims, suspects, court, courts, prosecution, isc |
| Topic 16 | energy, businesses, business, jobs, investment, economy, industry, economic, new, sector | carbon, renewable, renewables, solar, low-carbon, energy, feed-in, manufacturing, steel, businesses |
| Topic 17 | people, want, one, get, know, say, us, many, think, need | things, think, something, get, want, going, really, say, lot, go |
| Topic 18 | education, schools, school, children, training, skills, parents, teachers, students, young | schools, teachers, pupils, curriculum, sen, academies, ofsted, pupil, grammar, attainment |
| Topic 19 | constituency, city, people, many, years, work, centre, one, hull, great | fishermen, cod, hull, plymouth, maiden, fishing, fish, humber, fleetwood, tourism |
| Topic 20 | housing, homes, people, private, london, social, home, affordable, need, accommodation | rent, tenants, landlords, rented, homelessness, homeless, rents, tenancies, housing, tenancy |
| Topic 21 | tax, year, million, government, budget, cuts, cut, poverty, increase, billion | tax, obr, vat, millionaires, 50p, inflation, budget, fiscal, chancellor, cut |
| Topic 22 | food, post, office, rural, petition, offices, farmers, royal, mail, government | petition, farmers, petitioners, meat, cull, labelling, cattle, badger, culling, beef |
| Topic 23 | people, international, human, government, war, rights, country, un, conflict, world | syria, israel, civilians, palestinian, israeli, gaza, sri, holocaust, hatred, sierra |
| Topic 24 | bbc, media, online, internet, sport, access, digital, culture, clubs, football | bbc, games, olympic, gambling, bbc’s, copyright, lap-dancing, broadband, radio, internet |
| Topic 25 | local, authorities, funding, areas, services, council, community, authority, government, communities | local, authorities, funding, councils, grant, authority, formula, deprived, areas, partnership |
| Topic 26 | children, child, families, care, family, parents, violence, support, domestic, victims | trafficked, csa, same-sex, adopters, child, rape, marriages, marriage, sexual, couples |
| Topic 27 | planning, water, development, land, environment, site, sites, flood, environmental, area | forestry, biodiversity, masts, habitats, gypsy, flood, waterways, flooding, marine, mmo |
| Topic 28 | secretary, state, house, last, statement, report, said, now, question, answer | secretary, statement, state, confirm, official, answer, vol, state’s, letter, written |
| Topic 29 | parliament, wales, vote, commission, political, assembly, people, welsh, elected, charities | electoral, polling, gibraltar, voting, assembly, vote, votes, voter, ballot, elections |
| Topic 30 | can, make, ensure, agree, important, take, made, point, sure, welcome | agree, aware, sure, ensure, taking, lady, welcome, steps, point, make |

## 1.11 Discussion

There do not appear to be substantial or meaningful differences in the speaking styles of female Labour MPs selected through all women short lists when compared to their female colleagues selected through open short lists 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 has American developers, and the 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 a British context.

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](#ref-pitkin1967)) – 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](#ref-andeweg2005)) 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?

# 2 Appendix

## 2.1 Full topic model summary - K69

## A topic model with 69 topics, 81607 documents and a 115477 word dictionary.

## Topic 1 Top Words:  
## Highest Prob: secretary, state, tell, ministers, given, today, department   
## FREX: secretary, state, confirm, tell, ministers, state's, minister's   
## Lift: dhar, lowell, qatada's, #nationalistsconfused, 1135, 2.5bn, 36,500   
## Score: secretary, state, confirm, state's, tell, ministers, department   
## Topic 2 Top Words:  
## Highest Prob: safety, register, registration, indicated, registered, electoral, risk   
## FREX: registration, indicated, hse, canvass, register, gurkhas, safety   
## Lift: aps, hse, 10-litre, 13a, 14,940, 1760, 1867   
## Score: safety, registration, register, electoral, indicated, registered, hse   
## Topic 3 Top Words:  
## Highest Prob: make, sure, statement, progress, difference, northern, ireland   
## FREX: statement, make, sure, progress, ireland, representations, difference   
## Lift: 101269, 101548, 102938, 103414, 106583, 107305, 109413   
## Score: make, statement, progress, sure, ireland, northern, milton   
## Topic 4 Top Words:  
## Highest Prob: debt, water, credit, charges, pay, loan, loans   
## FREX: payday, loan, lenders, debts, loans, debt, charges   
## Lift: 1,021, 1,025, 1,106, 1,189, 1,273, 1,385, 1,413   
## Score: debt, water, payday, loan, loans, lenders, credit   
## Topic 5 Top Words:  
## Highest Prob: house, committee, parliament, leader, select, motion, parliamentary   
## FREX: select, leader, house, motion, committee, backbench, scrutiny   
## Lift: e-petitions, praying-against, sherlock, wednesdays, sittings, thursdays, 10,000-signature   
## Score: committee, house, leader, select, scrutiny, parliament, motion   
## Topic 6 Top Words:  
## Highest Prob: new, development, work, need, investment, strategy, must   
## FREX: development, strategy, develop, project, regional, projects, partnership   
## Lift: #1,150, 1.245, 1.875, 128406, 131,000, 18-the, 2002-around   
## Score: development, regional, investment, strategy, infrastructure, projects, work   
## Topic 7 Top Words:  
## Highest Prob: road, petition, residents, car, vehicles, petitioners, dogs   
## FREX: petitioners, lap-dancing, petition, dogs, dog, pedestrians, cycling   
## Lift: 0.037, 0.044, 0fficial, 1,042, 1,072, 1,108, 1,122   
## Score: petitioners, petition, dogs, road, residents, dog, declares   
## Topic 8 Top Words:  
## Highest Prob: important, agree, welcome, country, making, particularly, thank   
## FREX: agree, welcome, important, absolutely, makes, making, friend's   
## Lift: adequacies, and-importantly-much, ayse, ballantine, bobtail-and, bostrom, bucketfuls   
## Score: agree, important, thank, welcome, friend's, absolutely, country   
## Topic 9 Top Words:  
## Highest Prob: companies, market, company, competition, energy, consumers, prices   
## FREX: competition, companies, market, wholesale, suppliers, company, regulator   
## Lift: 1,105, 1,345, ashington, boakye, nord, over-charging, price-fixing   
## Score: companies, consumers, energy, market, company, prices, competition   
## Topic 10 Top Words:  
## Highest Prob: women, men, equality, women's, discrimination, rights, gender   
## FREX: gender, bishops, transgender, women's, women, abortion, same-sex   
## Lift: balmforth, bpas, celebrants, cohabitants, jessy, msafiri, natal   
## Score: women, women's, equality, men, gender, discrimination, marriage   
## Topic 11 Top Words:  
## Highest Prob: energy, climate, fuel, change, green, carbon, emissions   
## FREX: renewables, solar, insulation, feed-in, biofuels, greenhouse, dioxide   
## Lift: fossil, #2,500, #solar, 1-are, 1,129, 1,214, 1,343   
## Score: energy, fuel, carbon, emissions, climate, renewable, renewables   
## Topic 12 Top Words:  
## Highest Prob: office, post, offices, royal, service, closure, mail   
## FREX: offices, mail, sub-post, post, sub-postmasters, closures, consignia   
## Lift: #1.8, #210, #450, 1,001, 1,352, 1,639, 1,827   
## Score: post, offices, office, mail, closure, postal, sub-post   
## Topic 13 Top Words:  
## Highest Prob: mr, north, south, east, west, spoke, friends   
## FREX: ealing, spoke, dorset, lothian, ayrshire, glasgow, chris   
## Lift: argos's, blackford, cairns's, clemency, marxist, no2id, 0.66   
## Score: mr, east, north, south, west, spoke, birmingham   
## Topic 14 Top Words:  
## Highest Prob: pension, scheme, benefit, pensions, benefits, pensioners, system   
## FREX: pension, esa, pensions, claimants, retirement, pip, pensioners   
## Lift: means-testing, #20,000, #400, 0º, 1,052, 1,366, 1,482   
## Score: pension, pensions, pensioners, allowance, scheme, retirement, credit   
## Topic 15 Top Words:  
## Highest Prob: economy, jobs, economic, growth, unemployment, country, investment   
## FREX: unemployment, recession, growth, economy, obr, deficit, inflation   
## Lift: 0.76, 0.83, 1,196, 1,319, 1.04, 1.32, 10-about   
## Score: economy, jobs, unemployment, growth, economic, recession, chancellor   
## Topic 16 Top Words:  
## Highest Prob: schools, school, education, children, teachers, parents, pupils   
## FREX: academies, pupil, grammar, schools, pupils, teachers, ofsted   
## Lift: sen2, 11-plus, leas, pupil, 000-to, 1-regardless, 1,000-pupil   
## Score: schools, school, teachers, pupils, children, education, parents   
## Topic 17 Top Words:  
## Highest Prob: want, say, one, think, know, need, us   
## FREX: think, say, things, want, something, saying, going   
## Lift: about-part, arguing-i, beneficial-we, career-many, cause-the, clam, compatriot   
## Score: think, want, get, say, things, going, us   
## Topic 18 Top Words:  
## Highest Prob: review, report, commission, independent, process, recommendations, inquiry   
## FREX: recommendations, inquiry, panel, audit, independent, recommendation, reviews   
## Lift: bourn, cag's, clarke's, clowes, dg, emag, equitable's   
## Score: fsa, inquiry, review, commission, recommendations, report, independent   
## Topic 19 Top Words:  
## Highest Prob: business, businesses, small, financial, bank, banks, insurance   
## FREX: smes, medium-sized, businesses, bank, enterprises, enterprise, banking   
## Lift: 0.21, 0.84, 1,034, 1,130, 10-fold, 1130, 12.19   
## Score: businesses, business, bank, banks, banking, insurance, small   
## Topic 20 Top Words:  
## Highest Prob: wales, industry, welsh, north-east, england, assembly, constituency   
## FREX: welsh, wales, steel, cardiff, north-east, assembly, visteon   
## Lift: a55, angharad, bethesda, co-investment, dewhirst, dogger, gorge   
## Score: wales, welsh, assembly, manufacturing, steel, north-east, yorkshire   
## Topic 21 Top Words:  
## Highest Prob: care, services, social, mental, need, health, home   
## FREX: mental, care, social, elderly, older, advocacy, services   
## Lift: #900,000, 1,051, 1,312, 10,758, 104962, 1089, 13,198   
## Score: care, mental, services, social, health, older, homes   
## Topic 22 Top Words:  
## Highest Prob: pay, work, workers, employment, working, wage, minimum   
## FREX: wage, workers, zero-hours, employees, paternity, employer, minimum   
## Lift: 6.70, 8.20, 85p, awb, e-balloting, hannett, increments   
## Score: wage, workers, employers, employment, pay, employees, minimum   
## Topic 23 Top Words:  
## Highest Prob: amendment, clause, amendments, new, 1, lords, section   
## FREX: amendment, nos, insert, subsection, clause, amendments, clauses   
## Lift: 153a, 22a, 287, 50b, 51b, counter-notice, insured's   
## Score: clause, amendment, amendments, lords, nos, insert, subsection   
## Topic 24 Top Words:  
## Highest Prob: report, last, since, said, received, published, year   
## FREX: march, vol, official, january, july, november, published   
## Lift: 1-2ws, 1,033, 1,099, 1,124,818, 1,337, 1,368,186, 1,595   
## Score: report, official, vol, published, march, april, november   
## Topic 25 Top Words:  
## Highest Prob: made, clear, impact, decision, changes, recent, assessment   
## FREX: made, decision, assessment, clear, decisions, impact, implications   
## Lift: 104963, 107312, 116,400, 125214, 125828, 125830, 126370   
## Score: made, assessment, impact, changes, decision, decisions, clear   
## Topic 26 Top Words:  
## Highest Prob: funding, cuts, fund, cut, budget, grant, spending   
## FREX: flood, funding, bbc, formula, grant, flooding, floods   
## Lift: #10.89, #12, #3.3, #bbcdiversity, 1,027, 1,536-will, 1,546   
## Score: funding, cuts, flood, bbc, budget, spending, flooding   
## Topic 27 Top Words:  
## Highest Prob: money, spent, extra, spend, liberal, cost, spending   
## FREX: money, spent, liberal, spend, democrats, tories, tory   
## Lift: 1-but, 10,309.63, 1228, 158.8, 1763, 18-that, 1979-80   
## Score: money, liberal, tory, democrats, conservatives, tories, spending   
## Topic 28 Top Words:  
## Highest Prob: constituency, great, community, proud, many, sport, one   
## FREX: maiden, arts, football, museum, museums, sport, olympic   
## Lift: 0.27, 0.51, 1,084, 1,126, 1,468, 1,580-plus, 1,983   
## Score: arts, sport, museum, maiden, heritage, football, constituency   
## Topic 29 Top Words:  
## Highest Prob: families, child, poverty, children, parents, work, credit   
## FREX: lone, poverty, childcare, families, low-income, child, nursery   
## Lift: 1,000-discriminates, 1,000-not, 1,080, 1,142,600, 1,170, 1,390, 1,664   
## Score: poverty, child, families, children, parents, credit, lone   
## Topic 30 Top Words:  
## Highest Prob: party, conservative, vote, parliament, political, election, labour   
## FREX: party, vote, voting, conservative, party's, voters, election   
## Lift: alphabetical, gentry, olga, one-party, randomisation, 1,166, 1,294   
## Score: party, conservative, vote, scottish, election, elections, political   
## Topic 31 Top Words:  
## Highest Prob: point, can, may, issue, take, however, whether   
## FREX: matter, point, understand, consider, certainly, accept, possible   
## Lift: 450,000-in, advised-by, backslid, bill-albeit, bizarre-but, can-enable, cases-roughly   
## Score: point, matter, issue, gentleman's, consider, shall, whether   
## Topic 32 Top Words:  
## Highest Prob: member, said, lady, mentioned, raised, comments, speech   
## FREX: member, lady, comments, remarks, bromley, interesting, chislehurst   
## Lift: 12.20, 130b, 1991-forcing, 2,784, 54,000-worth, achieved-is, arguments-and   
## Score: member, lady, comments, said, speech, raised, points   
## Topic 33 Top Words:  
## Highest Prob: european, uk, eu, countries, united, union, europe   
## FREX: accession, enlargement, wto, lisbon, treaty, eu, doha   
## Lift: 13652, 13653, 13654, 1707, balkan, barnier, blackmailing   
## Score: eu, european, countries, union, treaty, europe, trade   
## Topic 34 Top Words:  
## Highest Prob: education, skills, young, training, students, university, college   
## FREX: ema, fe, students, apprenticeship, universities, qualifications, apprenticeships   
## Lift: ema, #ne, 1,188, 1,308, 1,555-what, 1,740, 1,803   
## Score: students, education, young, skills, apprenticeships, training, universities   
## Topic 35 Top Words:  
## Highest Prob: local, authorities, authority, planning, community, communities, councils   
## FREX: authorities, local, authority, planning, councils, councillors, locally   
## Lift: achcew, central-local, laa, lsp, maas, observances, place-shaping   
## Score: local, authorities, authority, councils, planning, communities, community   
## Topic 36 Top Words:  
## Highest Prob: disabled, carers, disability, support, disabilities, needs, caring   
## FREX: carers, autism, autistic, disabled, disabilities, disability, dementia   
## Lift: autism, rnib, #185, #85, #hellomynameis, 1,400-one, 10-person   
## Score: carers, disabled, disability, autism, disabilities, caring, dementia   
## Topic 37 Top Words:  
## Highest Prob: environment, marine, fishing, sea, industry, natural, fish   
## FREX: fishermen, cod, forestry, biodiversity, habitats, mmo, fishing   
## Lift: aquaculture, arable, bee-friendly, biodiversity, birdlife, bycatch, caterpillar   
## Score: marine, fishing, fishermen, fish, fisheries, wildlife, conservation   
## Topic 38 Top Words:  
## Highest Prob: justice, court, violence, victims, cases, criminal, domestic   
## FREX: attorney-general, defendants, defendant, prison, prosecutors, solicitor-general, stalking   
## Lift: #9, 0.08, 0.48, 1,046, 1,237, 10,544, 10.15   
## Score: violence, prison, court, offence, criminal, rape, victims   
## Topic 39 Top Words:  
## Highest Prob: international, foreign, rights, human, peace, un, conflict   
## FREX: israel, palestinian, israeli, gaza, sri, zimbabwe, iran   
## Lift: lankan, saddam, #aleppo, 1,010, 1,476, 1,591, 1224   
## Score: un, israel, syria, humanitarian, palestinian, israeli, iraq   
## Topic 40 Top Words:  
## Highest Prob: day, family, never, told, families, life, happened   
## FREX: man, died, son, story, stories, hillsborough, tragedy   
## Lift: 10,000-seat, 12-inch, 1234, 1519-20, 1635, 1710, 174,995   
## Score: families, holocaust, family, constituent, man, died, mother   
## Topic 41 Top Words:  
## Highest Prob: proposals, future, forward, consultation, plans, meet, paper   
## FREX: proposals, consultation, paper, plans, forward, discuss, white   
## Lift: 10.42, 107910, 109648, 114061, 119621, 141605, 141607   
## Score: proposals, consultation, plans, future, forward, paper, white   
## Topic 42 Top Words:  
## Highest Prob: behaviour, crime, antisocial, alcohol, young, drugs, drug   
## FREX: antisocial, asbos, alcohol, alcohol-related, binge, psychoactive, drinking   
## Lift: acquisitive, addaction, auto, bailes, crawlers, ghb, gilpin   
## Score: antisocial, crime, behaviour, alcohol, drug, drugs, cannabis   
## Topic 43 Top Words:  
## Highest Prob: housing, homes, social, affordable, private, home, accommodation   
## FREX: housing, tenants, rented, tenancies, homelessness, leasehold, landlords   
## Lift: one-for-one, one-bedroom, rented, right-to-buy, #19, #21.5, #28.5   
## Score: housing, homes, tenants, rented, rent, landlords, affordable   
## Topic 44 Top Words:  
## Highest Prob: question, order, mr, put, asked, answer, questions   
## FREX: question, answer, questions, speaker, asked, deputy, answers   
## Lift: 11.00, 11.57, 12.26, 1223, 1232, 1412, 1555-56   
## Score: question, speaker, mr, answer, deputy, order, questions   
## Topic 45 Top Words:  
## Highest Prob: research, cancer, treatment, medical, condition, screening, disease   
## FREX: embryos, prostate, cervical, hepatitis, cloning, transplant, embryo   
## Lift: abnormalities, cystic, embryo, fertilisation, marrow, @cfaware, #500   
## Score: cancer, patients, embryos, screening, treatment, tissue, breast   
## Topic 46 Top Words:  
## Highest Prob: online, internet, farmers, animals, digital, animal, broadband   
## FREX: cull, badgers, badger, fur, bovine, mink, culling   
## Lift: culling, @daisydumble, @donna\_smiley, @jimspin, @leamingtonsbc, @maggieannehayes, @nhconsortium   
## Score: farmers, animals, internet, cull, animal, online, badgers   
## Topic 47 Top Words:  
## Highest Prob: defence, forces, armed, plymouth, personnel, service, military   
## FREX: mod, naval, hms, submarines, dockyard, veterans, armed   
## Lift: hms, submarine, submarines, 1,000-people, 1,625, 1,705, 10-3   
## Score: defence, armed, forces, plymouth, military, personnel, mod   
## Topic 48 Top Words:  
## Highest Prob: information, home, security, data, immigration, control, orders   
## FREX: extradition, tpims, sia, warrant, detention, checks, tpim   
## Lift: carlile's, carlile, sia, 10-month, 10,410, 10,500-for, 10.45   
## Score: immigration, terrorism, detention, terrorist, tpims, home, security   
## Topic 49 Top Words:  
## Highest Prob: police, officers, crime, policing, home, force, service   
## FREX: constable, constables, officers, policing, police, soca, ipcc   
## Lift: 2003-morecambe, 9,650, a19s, ashleys, bigg, bounties, ckp   
## Score: police, officers, policing, crime, forces, constable, neighbourhood   
## Topic 50 Top Words:  
## Highest Prob: nhs, hospital, patients, health, services, hospitals, care   
## FREX: dentists, dentistry, pharmacies, pct, nhs, hospitals, hospital   
## Lift: acos, bequest, bernstein, bodmin, catto, cayton, chailey   
## Score: nhs, patients, hospital, health, patient, hospitals, care   
## Topic 51 Top Words:  
## Highest Prob: tax, budget, cut, chancellor, cuts, rate, income   
## FREX: 50p, vat, millionaires, hit, tax, allowances, credits   
## Lift: #840, 0.76p, 1,003, 1,009, 1,226, 1,275, 1,296   
## Score: tax, vat, budget, credits, chancellor, cuts, income   
## Topic 52 Top Words:  
## Highest Prob: years, now, two, time, first, three, past   
## FREX: years, three, months, ago, two, past, weeks   
## Lift: 10-week-old, 10,616, 11-month, 11-point, 1758, 196b, 63,500   
## Score: years, months, two, ago, three, past, weeks   
## Topic 53 Top Words:  
## Highest Prob: staff, doctors, emergency, medical, service, training, nurses   
## FREX: ambulance, junior, staffing, doctors, halifax, posts, nurses   
## Lift: #i'm, 03, 1-who, 1,454, 1,631, 10,000-strong, 10,000-with   
## Score: staff, doctors, ambulance, nurses, medical, emergency, junior   
## Topic 54 Top Words:  
## Highest Prob: bill, legislation, act, law, rights, provisions, powers   
## FREX: bill, legislation, bill's, provisions, passage, regulations, legislative   
## Lift: 1865, 1990s-when, 1998-it, 19may2000, 2003-largely, 2005-have, 29-year   
## Score: bill, legislation, provisions, rights, law, powers, regulations   
## Topic 55 Top Words:  
## Highest Prob: public, sector, private, organisations, service, voluntary, services   
## FREX: public, voluntary, organisations, sector, private, co-operative, volunteering   
## Lift: 1844, af, carpetbaggers, nebulous, puk, 1075, 170-year   
## Score: public, sector, private, voluntary, organisations, service, services   
## Topic 56 Top Words:  
## Highest Prob: health, national, inequalities, programme, suicide, disease, department   
## FREX: flu, hiv, pandemic, inequalities, infections, suicide, mortality   
## Lift: kirkley, lowestoft, nihr, acupuncture, influenza, #148, #3.6   
## Score: health, vaccine, flu, inequalities, hiv, infection, suicide   
## Topic 57 Top Words:  
## Highest Prob: council, london, areas, city, area, constituency, centre   
## FREX: county, mayor, borough, cities, liverpool, city, regeneration   
## Lift: #12,000, #14.4, #356, #38, #5,000, #500,000, #66.6   
## Score: london, council, city, regeneration, county, rural, borough   
## Topic 58 Top Words:  
## Highest Prob: advice, legal, cases, civil, hull, aid, case   
## FREX: hull, tribunal, legal, compensation, solicitors, advice, concentrix   
## Lift: 0300, 1,997, 1.148, 1.4m, 112.8, 1147, 128,687   
## Score: legal, advice, hull, aid, compensation, civil, tribunal   
## Topic 59 Top Words:  
## Highest Prob: people, work, many, young, get, people's, can   
## FREX: people, people's, get, getting, work, young, jobcentre   
## Lift: 2,425, 294,488, 3,699, 37,290, 5,320, 50-to-64, 75589   
## Score: people, young, work, get, youth, many, people's   
## Topic 60 Top Words:  
## Highest Prob: tax, revenue, relief, duty, uk, avoidance, hmrc   
## FREX: evasion, hmrc, gaar, avoidance, inland, stamp, revenue   
## Lift: 1,643, 3.12, 32.2, 44a, 80g, aaronson, aat   
## Score: tax, hmrc, avoidance, revenue, relief, evasion, territories   
## Topic 61 Top Words:  
## Highest Prob: government, government's, policy, labour, previous, scotland, scottish   
## FREX: government, previous, policy, government's, scotland, coalition, scottish   
## Lift: 2005-perhaps, 80994, actually-that, agency-when, agenda-access, alloway, aware-in   
## Score: government, scotland, scottish, labour, policy, government's, previous   
## Topic 62 Top Words:  
## Highest Prob: trafficking, home, uk, asylum, refugees, immigration, country   
## FREX: trafficking, slavery, trafficked, sierra, leone, slave, dubs   
## Lift: #7, 0.025, 1-yes, 1,060, 1,483, 1,746, 1.123   
## Score: trafficking, refugees, asylum, slavery, trafficked, immigration, sierra   
## Topic 63 Top Words:  
## Highest Prob: food, products, industry, smoking, advertising, tobacco, ban   
## FREX: gambling, betting, sunbed, tobacco, cocoa, meat, supermarkets   
## Lift: 0.7p, 00, 0157, 1,000-almost, 1,032, 1,200-i, 1,666   
## Score: food, smoking, products, tobacco, advertising, gambling, industry   
## Topic 64 Top Words:  
## Highest Prob: members, debate, many, issues, also, today, heard   
## FREX: members, debate, heard, speak, sides, issues, hear   
## Lift: noakes, 6.47pm, accept-or, analysis-but, aspect-listening-is, bunfight, called-making   
## Score: members, debate, issues, many, opposition, heard, constituents   
## Topic 65 Top Words:  
## Highest Prob: children, child, parents, young, children's, family, contact   
## FREX: csa, adopters, adoption, child's, cafcass, looked-after, children's   
## Lift: csa, @mandatenow, 10-month-old, 10-went, 12j, 150765, 16-only   
## Score: children, child, parents, young, children's, adoption, child's   
## Topic 66 Top Words:  
## Highest Prob: transport, rail, bus, services, line, travel, train   
## FREX: rail, passengers, passenger, heathrow, hs2, freight, high-speed   
## Lift: 12-car, 15.15, 50.1, adtranz, anti-icing, bahn, chilterns   
## Score: rail, transport, bus, passengers, fares, trains, hs2   
## Topic 67 Top Words:  
## Highest Prob: year, million, number, increase, figures, increased, billion   
## FREX: million, figures, figure, increased, increase, compared, year   
## Lift: #112, #3,850, #84.3, #87.2, 1,249, 102269, 122.9   
## Score: million, year, billion, increase, figures, average, increased   
## Topic 68 Top Words:  
## Highest Prob: support, ensure, can, help, aware, taking, take   
## FREX: aware, ensure, support, taking, steps, continue, help   
## Lift: 103684, 103965, 107320, 111532, 112584, 113698, 117890   
## Score: support, ensure, steps, aware, help, taking, department   
## Topic 69 Top Words:  
## Highest Prob: deal, recently, new, can, lack, great, concern   
## FREX: deal, recently, lack, elsewhere, concern, great, improved   
## Lift: 2004-a, 721,000, added-gva-per, age-of, centres-jacs-which, employment-can, index-the   
## Score: deal, recently, new, worktrack, lack, can, great

## 2.2 Full topic model estimate summary - K69

##   
## Call:  
## estimateEffect(formula = 1:69 ~ short\_list, stmobj = topic\_model2,   
## metadata = lab\_corpus\_fem\_stm$meta, uncertainty = "Global")  
##   
##   
## Topic 1:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0170452 0.0002908 58.62 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0069023 0.0003494 19.75 <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) 0.0058941 0.0002418 24.37 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0007101 0.0003035 2.34 0.0193 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 3:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0087131 0.0001123 77.61 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0002145 0.0001469 1.46 0.144   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 4:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0064753 0.0003061 21.157 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0036213 0.0003916 9.249 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 5:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0120613 0.0002563 47.06 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0035427 0.0003340 10.61 <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) 0.0313835 0.0004275 73.42 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0093880 0.0004930 -19.04 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 7:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0082016 0.0003862 21.238 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0024199 0.0004803 5.038 0.000000471 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 8:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0155972 0.0001346 115.846 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0006670 0.0001461 -4.565 0.000005 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 9:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0106936 0.0002672 40.016 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0025223 0.0003459 -7.291 0.00000000000031 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 10:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0147976 0.0004511 32.801 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0002600 0.0005639 0.461 0.645   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 11:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0131094 0.0004321 30.337 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0009008 0.0005137 -1.753 0.0795 .   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 12:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0100368 0.0003289 30.517 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0026467 0.0003780 -7.002 0.00000000000254 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 13:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0084721 0.0002283 37.117 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0015047 0.0002952 5.097 0.000000345 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 14:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0133812 0.0004662 28.70 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0060907 0.0005569 10.94 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 15:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0169598 0.0004328 39.184 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0029739 0.0005230 5.686 0.000000013 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 16:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0135165 0.0005236 25.814 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0032615 0.0006749 4.833 0.00000135 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 17:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0425063 0.0003180 133.678 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0008118 0.0003886 2.089 0.0367 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 18:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0268588 0.0004970 54.04 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0068270 0.0005953 -11.47 <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) 0.0129067 0.0003249 39.728 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0016970 0.0003787 -4.481 0.00000743 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 20:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0086123 0.0003466 24.85 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0060597 0.0004405 13.76 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 21:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0124554 0.0003103 40.144 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0011195 0.0003979 -2.813 0.0049 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 22:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0127285 0.0003160 40.284 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0008351 0.0003998 2.089 0.0367 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 23:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0185821 0.0005546 33.504 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0028032 0.0006219 -4.507 0.00000657 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 24:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0138654 0.0002277 60.901 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0013366 0.0002836 4.714 0.00000244 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 25:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0111240 0.0001353 82.236 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0007913 0.0001690 4.683 0.00000284 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 26:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0098056 0.0002856 34.334 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0037690 0.0003821 9.865 <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) 0.0103147 0.0002153 47.898 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0009083 0.0002716 3.344 0.000825 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 28:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0111674 0.0004014 27.823 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0027980 0.0005113 5.472 0.0000000447 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 29:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0105159 0.0003561 29.532 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0042201 0.0004452 9.479 <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) 0.0169408 0.0004432 38.223 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0007967 0.0005591 1.425 0.154   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 31:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0369138 0.0002209 167.1 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0068082 0.0002801 -24.3 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 32:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0100375 0.0001339 74.976 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0002564 0.0001601 -1.601 0.109   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 33:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0230357 0.0005115 45.031 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0059630 0.0006442 -9.257 <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) 0.0136757 0.0004476 30.555 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0011014 0.0005612 1.963 0.0497 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 35:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0198297 0.0003372 58.81 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0061427 0.0003952 -15.54 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 36:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0061177 0.0003195 19.15 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0041057 0.0004090 10.04 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 37:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0069647 0.0003207 21.720 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0015038 0.0004226 3.559 0.000373 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 38:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0226399 0.0005278 42.90 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0073545 0.0006041 -12.18 <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) 0.0205450 0.0006362 32.295 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0011703 0.0008261 1.417 0.157   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 40:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0139286 0.0003536 39.39 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0047476 0.0004496 10.56 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 41:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0107924 0.0001185 91.06 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0014800 0.0001354 -10.93 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 42:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0150546 0.0004409 34.144 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0033588 0.0005521 -6.083 0.00000000118 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 43:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0140213 0.0004927 28.459 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0021746 0.0006107 3.561 0.00037 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 44:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0147178 0.0002669 55.153 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0016359 0.0003348 4.886 0.00000103 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 45:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0135478 0.0004593 29.496 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0036884 0.0005404 -6.826 0.0000000000088 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 46:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0067846 0.0003642 18.630 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0042913 0.0004450 9.644 <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) 0.0077616 0.0003501 22.173 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0027567 0.0004392 6.276 0.00000000035 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 48:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0225109 0.0005004 44.98 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0077208 0.0005744 -13.44 <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) 0.0155691 0.0004815 32.334 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0038720 0.0005871 -6.595 0.0000000000427 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 50:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0232426 0.0006458 35.99 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0076599 0.0007414 -10.33 <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) 0.0105812 0.0003547 29.83 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0055797 0.0004455 12.53 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 52:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.01749066 0.00018421 94.949 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.00001861 0.00022700 0.082 0.935   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 53:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0107616 0.0003976 27.069 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0003040 0.0004713 0.645 0.519   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 54:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0261056 0.0004287 60.895 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0045012 0.0004954 -9.087 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 55:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0101860 0.0001866 54.575 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0004785 0.0002396 -1.997 0.0459 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 56:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0114038 0.0003564 31.993 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0015353 0.0004426 -3.469 0.000524 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 57:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0129092 0.0003204 40.295 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0012897 0.0004077 3.163 0.00156 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 58:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0090842 0.0002421 37.516 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0015920 0.0003309 4.811 0.00000151 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 59:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0166452 0.0001952 85.255 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0007304 0.0002367 3.086 0.00203 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 60:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0100737 0.0003804 26.481 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0002325 0.0004656 -0.499 0.618   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 61:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0112635 0.0001126 100.00 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0019048 0.0001386 13.74 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 62:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0104546 0.0003979 26.272 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0010332 0.0004741 -2.179 0.0293 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 63:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0088025 0.0003595 24.484 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0020157 0.0004612 4.371 0.0000124 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 64:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0207853 0.0002314 89.841 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0017451 0.0003057 5.709 0.0000000114 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 65:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0136868 0.0003796 36.054 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0017375 0.0004538 -3.829 0.000129 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 66:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0132126 0.0004858 27.20 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0037747 0.0005870 6.43 0.000000000128 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 67:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0219868 0.0003104 70.828 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0011566 0.0003880 -2.981 0.00287 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 68:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0193961 0.0001791 108.29 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0026859 0.0002288 -11.74 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 69:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.00275121 0.00002013 136.706 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.00002551 0.00002600 -0.981 0.327   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 2.3 Full topic model summary - K30

## A topic model with 30 topics, 81607 documents and a 115477 word dictionary.

## Topic 1 Top Words:  
## Highest Prob: bill, amendment, clause, new, legislation, amendments, act   
## FREX: amendment, clause, amendments, clauses, nos, insert, subsection   
## 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: issues, public, information, also, report, review, process   
## FREX: consultation, review, guidance, recommendations, information, considering, decisions   
## Lift: 1-who, 1,842, 109648, 1402, 151387, 1981-was, 1a-has   
## Score: consultation, guidance, information, review, committee, issues, process   
## Topic 3 Top Words:  
## Highest Prob: women, men, pay, equality, rights, women's, discrimination   
## FREX: women, equality, gender, equalities, bishops, discrimination, female   
## Lift: gender, #112, #neverthelesshepersisted, 1-breast-feed, 1,087, 1,574, 1.57   
## Score: women, women's, equality, men, gender, discrimination, girls   
## Topic 4 Top Words:  
## Highest Prob: police, crime, officers, behaviour, policing, home, antisocial   
## FREX: policing, antisocial, constable, burglary, wardens, crime, constabulary   
## Lift: 1,113, 1.24, 17,614, acpo's, adz, alcohol-free, alleygator   
## Score: police, crime, officers, policing, antisocial, behaviour, constable   
## Topic 5 Top Words:  
## Highest Prob: european, uk, countries, eu, union, trade, international   
## FREX: treaty, enlargement, wto, lisbon, doha, eu, eu's   
## Lift: #420, 0.26, 0.56, 07, 09, 1-2, 1-of   
## Score: eu, european, countries, treaty, armed, defence, forces   
## Topic 6 Top Words:  
## Highest Prob: transport, london, rail, bus, road, services, line   
## FREX: rail, bus, passengers, fares, trains, buses, passenger   
## Lift: #145, 0.1p, 0.45, 0.86, 1-very, 1,122, 1,658   
## Score: rail, transport, bus, passengers, fares, trains, congestion   
## Topic 7 Top Words:  
## Highest Prob: people, work, benefit, pension, benefits, support, disabled   
## FREX: disabled, jobcentre, incapacity, carers, pension, claimants, esa   
## Lift: dla, #400, 0300, 1-to-1, 1,030, 1,052, 1,366   
## Score: pension, carers, disabled, pensions, allowance, disability, credit   
## Topic 8 Top Words:  
## Highest Prob: immigration, safety, uk, asylum, enforcement, home, number   
## FREX: dogs, dog, id, visa, fur, mink, hse   
## Lift: 44a, a8, acoba, arcs, attachment-free, bareboat, bonfires   
## Score: immigration, asylum, animals, dogs, fireworks, dog, animal   
## Topic 9 Top Words:  
## Highest Prob: health, research, cancer, treatment, medical, disease, can   
## FREX: cancer, diseases, vaccine, flu, embryos, infections, diabetes   
## Lift: 1169, 20-fold, ablation, abnormalities, adpkd, aed, anaesthesia   
## Score: cancer, patients, disease, smoking, health, diagnosis, screening   
## Topic 10 Top Words:  
## Highest Prob: government, labour, conservative, party, opposition, policy, government's   
## FREX: conservative, liberal, democrats, conservatives, scottish, democrat, scotland   
## Lift: #nationalistsconfused, 1-but, 1.135, 10,182, 10.91, 1125, 116385   
## Score: conservative, scottish, party, labour, government, scotland, liberal   
## Topic 11 Top Words:  
## Highest Prob: care, health, nhs, services, service, hospital, patients   
## FREX: dentists, ambulance, dentistry, helier, dentist, nurses, hospital   
## Lift: 2.24, 2005-6, 22,600, 422, 5.45pm, 8.03, 8.41   
## Score: nhs, patients, care, hospital, health, patient, hospitals   
## Topic 12 Top Words:  
## Highest Prob: member, members, debate, house, mr, committee, said   
## FREX: member, speaker, mr, debate, spoke, thoughtful, backbench   
## Lift: e-petitions, @daisydumble, @percyblakeney63, 10,000-signature, 1028, 1080, 11.00   
## Score: member, mr, committee, members, speaker, debate, house   
## Topic 13 Top Words:  
## Highest Prob: companies, financial, company, market, scheme, money, debt   
## FREX: payday, annuity, oft, policyholders, penrose, fca, loan   
## Lift: fca, oft, prepayment, #1.8, #20,000, 0.21, 0.84   
## Score: companies, consumers, fsa, banks, company, customers, consumer   
## Topic 14 Top Words:  
## Highest Prob: young, people, health, mental, youth, prison, problems   
## FREX: prisons, probation, cannabis, reoffending, mental, prison, self-harm   
## Lift: cannabis, hawton, poppers, camhs, inmates, reoffending, #230   
## Score: young, mental, prison, drugs, alcohol, youth, drug   
## Topic 15 Top Words:  
## Highest Prob: cases, court, legal, law, case, justice, evidence   
## FREX: judicial, attorney-general, defendant, extradition, tpims, suspects, court   
## Lift: 110-day, abscond, absconded, acquittals, adduce, anti-viral, babar   
## Score: court, offence, courts, criminal, justice, prosecution, offences   
## Topic 16 Top Words:  
## Highest Prob: energy, businesses, business, jobs, investment, economy, industry   
## FREX: carbon, renewable, renewables, solar, low-carbon, energy, feed-in   
## Lift: fossil, sellafield, viyella, energy-intensive, low-carbon, #12.5, #140,000   
## Score: energy, businesses, jobs, economy, manufacturing, industry, investment   
## Topic 17 Top Words:  
## Highest Prob: people, want, one, get, know, say, us   
## FREX: things, think, something, get, want, going, really   
## Lift: 1,027, 2.85, 30s-will, 6.37, 778, about-part, accept-there   
## Score: people, get, think, things, going, want, say   
## Topic 18 Top Words:  
## Highest Prob: education, schools, school, children, training, skills, parents   
## FREX: schools, teachers, pupils, curriculum, sen, academies, ofsted   
## Lift: ema, #8,000, 1,000-pupil, 1,051, 1,100-i, 1,170, 1,204   
## Score: schools, school, education, children, teachers, pupils, students   
## Topic 19 Top Words:  
## Highest Prob: constituency, city, people, many, years, work, centre   
## FREX: fishermen, cod, hull, plymouth, maiden, fishing, fish   
## Lift: #14.4, #66.6, 0.27, 0.51, 1,084, 1,126, 1.41   
## Score: plymouth, constituency, hull, city, fishing, fish, arts   
## Topic 20 Top Words:  
## Highest Prob: housing, homes, people, private, london, social, home   
## FREX: rent, tenants, landlords, rented, homelessness, homeless, rents   
## Lift: right-to-buy, #19, #21.5, #28.5, 1,000-odd, 1,026, 1,083   
## Score: housing, homes, rented, rent, tenants, landlords, affordable   
## Topic 21 Top Words:  
## Highest Prob: tax, year, million, government, budget, cuts, cut   
## FREX: tax, obr, vat, millionaires, 50p, inflation, budget   
## Lift: 0.38, 1,869, 107,500, 11.2, 13,600, 2,073, 2.33   
## Score: tax, cuts, budget, poverty, chancellor, unemployment, billion   
## Topic 22 Top Words:  
## Highest Prob: food, post, office, rural, petition, offices, farmers   
## FREX: petition, farmers, petitioners, meat, cull, labelling, cattle   
## Lift: #450, 1072, 11,900, 12-point, 934, a690, ablewell   
## Score: food, farmers, petitioners, petition, post, rural, offices   
## Topic 23 Top Words:  
## Highest Prob: people, international, human, government, war, rights, country   
## FREX: syria, israel, civilians, palestinian, israeli, gaza, sri   
## Lift: muslims, #aleppo, #no2lgbthate, 0.002, 1,000-almost, 1,010, 1,019   
## Score: syria, un, israel, humanitarian, iraq, palestinian, israeli   
## Topic 24 Top Words:  
## Highest Prob: bbc, media, online, internet, sport, access, digital   
## FREX: bbc, games, olympic, gambling, bbc's, copyright, lap-dancing   
## Lift: age-restricted, age-verification, aquatics, bacta, bandwidth, bbfc, bduk   
## Score: bbc, sport, tickets, internet, digital, online, football   
## Topic 25 Top Words:  
## Highest Prob: local, authorities, funding, areas, services, council, community   
## FREX: local, authorities, funding, councils, grant, authority, formula   
## Lift: 416,000, 596,000, 82-3, 885, allison's, baccy, bellwin   
## Score: local, authorities, funding, councils, authority, council, services   
## Topic 26 Top Words:  
## Highest Prob: children, child, families, care, family, parents, violence   
## FREX: trafficked, csa, same-sex, adopters, child, rape, marriages   
## Lift: @mandatenow, 1-regardless, 1,000-discriminates, 1,142,600, 1,483, 1,746, 10-month-old   
## Score: child, children, parents, violence, care, sexual, rape   
## Topic 27 Top Words:  
## Highest Prob: planning, water, development, land, environment, site, sites   
## FREX: forestry, biodiversity, masts, habitats, gypsy, flood, waterways   
## Lift: biodiversity, encampments, masts, #tartantories, 0fficial, 1,000-year-old, 1,251   
## Score: planning, land, flood, marine, sites, water, site   
## Topic 28 Top Words:  
## Highest Prob: secretary, state, house, last, statement, report, said   
## FREX: secretary, statement, state, confirm, official, answer, vol   
## Lift: 12.40, ashleys, ayia, burne, cabinet's, cairns's, clutha   
## Score: secretary, state, statement, answer, confirm, inquiry, leader   
## Topic 29 Top Words:  
## Highest Prob: parliament, wales, vote, commission, political, assembly, people   
## FREX: electoral, polling, gibraltar, voting, assembly, vote, votes   
## Lift: @leamingtonsbc, @maggieannehayes, @nhconsortium, #keeptweeting, 1-46, 1-would, 1,294   
## Score: electoral, vote, elections, wales, assembly, referendum, welsh   
## Topic 30 Top Words:  
## Highest Prob: can, make, ensure, agree, important, take, made   
## FREX: agree, aware, sure, ensure, taking, lady, welcome   
## Lift: 1565, 19602, 2,095, 42931, 94254, agencies-an, anguish-filled   
## Score: agree, aware, thank, ensure, point, lady, can

## 2.4 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) 0.0449638 0.0006438 69.842 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0068672 0.0008151 -8.425 <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) 0.0757416 0.0006094 124.28 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0214999 0.0007156 -30.04 <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) 0.0230270 0.0006094 37.787 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0007379 0.0007006 -1.053 0.292   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 4:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0289307 0.0006532 44.289 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0074356 0.0007553 -9.845 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 5:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0368439 0.0006692 55.06 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0051042 0.0007841 -6.51 0.0000000000757 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 6:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0217908 0.0005613 38.83 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0054421 0.0007476 7.28 0.000000000000337 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 7:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0298354 0.0006479 46.05 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0131773 0.0007856 16.77 <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) 0.0186000 0.0004898 37.973 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0004554 0.0006359 0.716 0.474   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 9:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0249458 0.0005929 42.074 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0050996 0.0007240 -7.043 0.00000000000189 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 10:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0378833 0.0004773 79.37 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0020093 0.0005963 3.37 0.000753 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 11:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0407971 0.0006935 58.829 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0083294 0.0008737 -9.534 <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) 0.0389846 0.0006007 64.90 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0082293 0.0007327 11.23 <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) 0.0302331 0.0006106 49.510 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0028600 0.0007706 -3.712 0.000206 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 14:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0239247 0.0005278 45.327 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0032081 0.0006318 -5.078 0.000000383 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 15:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0409492 0.0006960 58.84 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0167525 0.0008539 -19.62 <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) 0.0384090 0.0006710 57.240 < 0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0045928 0.0008758 -5.244 0.000000158 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 17:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0788569 0.0005753 137.081 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0019895 0.0007255 2.742 0.00611 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 18:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0298463 0.0006798 43.904 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0038152 0.0008380 4.552 0.00000531 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 19:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0196034 0.0005043 38.87 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0092585 0.0006681 13.86 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 20:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0204482 0.0005550 36.846 < 0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0038414 0.0007558 5.083 0.000000373 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 21:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0460894 0.0007979 57.76 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0142923 0.0010054 14.22 <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) 0.0139632 0.0004680 29.839 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0055227 0.0005749 9.606 <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) 0.0261634 0.0006814 38.396 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0007600 0.0008556 0.888 0.374   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 24:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0124080 0.0003924 31.622 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0049014 0.0004998 9.807 <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) 0.0426118 0.0006124 69.58 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0085885 0.0007424 -11.57 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 26:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.02500670 0.00055723 44.877 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.00001744 0.00071917 -0.024 0.981   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 27:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0149404 0.0004813 31.044 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0003269 0.0005994 0.545 0.586   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Topic 28:  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0426959 0.0005816 73.41 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0145563 0.0007162 20.33 <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) 0.0187907 0.0005308 35.402 <0.0000000000000002 \*\*\*  
## short\_listTRUE 0.0063121 0.0006965 9.063 <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) 0.0526710 0.0003231 163.010 <0.0000000000000002 \*\*\*  
## short\_listTRUE -0.0037462 0.0003939 -9.509 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 2.5 AWS References to Constituents in Context

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* 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)”.[↩](#fnref1)
* Special Educational Needs[↩](#fnref2)