All Women Short lists Methodology

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Table 1: 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

1 Descriptive Statistics

Data in Table 1 is from House of Commons Library reports (Audickas, Hawkins, & Cracknell, 2017; Kelly, 2016). All women short lists were not used by Labour during the 2001 General Election.

2 Methodology

Previous research on gender differences in political speech patterns has focused on differences between male and female politicians (Yu, 2014) or on variations in Hilary Clinton's speech patterns (Bligh, Merolla, Schroedel, & Gonzalez, 2010; Jones, 2016). This paper focuses on differences in speech patterns between female Labour MPs nominated through All Women Shortlists (AWS) and female Labour MPs nominated through open short lists. We examined differences in speaking styles using the `Linguistic Inquiry and Word Count 2015` (LIWC) dictionary (Pennebaker, Boyd, Jordan, & Blackburn, 2015) and the `spaCy` (Honnibal & Montani, 2017) Parts-of-Speech (POS) tagger. We examined differences in the topics discussed by AWS and non-AWS MPs, using χ^2 tests for individual words and for bigrams. We trained a Naive Bayes classifier to distinguish AWS and non-AWS speeches. We used structured topic models (STM) to identify the topics discussed by AWS and non-AWS MPs.

To account for the possible effects of age, parliamentary experience and cohort, and in order to compare women selected through all women 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] Speeches and data on MPs' gender and party affiliation are from a previously assembled dataset (Odell, 2018). Information on candidates selected through all women short lists is from the House of Commons Library (Kelly, 2016). 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.

2.1 Linguistic Inquiry and Word Coun

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

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

Table 2: Number of Speeches and Words in Dataset

Gender	Speeches	Words
All	656,412	111,180,398
Female	148,702	26,231,034
Male	507,710	84,949,364
Conservatives		
All	285,291	44,800,169
Female	48,768	7,363,031
Male	236,523	37,437,138
Labour		
All	261,942	46,494,850
Female	84,569	15,897,929
Non-All Women Shortlists	28,695	5,422,776
All Women Shortlists	55,874	10,475,153
Male	177,373	30,596,921
Liberal Democrat		
All	72,716	13,485,902
Female	7,552	1,503,459
Male	65,164	11,982,443
Other		
All	36,463	6,399,477
Female	7,813	1,466,615
Male	28,650	4,932,862

Following Yu (2014) drawing on Newman, Groom, Handelman, & Pennebaker (2008) 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), calculated using `Quanteda` (Benoit, 2018) and `stringi` (Gagolewski, 2018).

Table 3: Effect Sizes for Male and Female Labour MPs

	Women		Men		Effect Size	
	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Pronouns	10.07	4.60	10.15	4.99	0.02	negligible
First person singular pronouns	1.89	2.41	2.02	2.55	0.05	negligible
First person plural pronouns	0.97	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

2.2 Women vs Men

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

2.3 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.

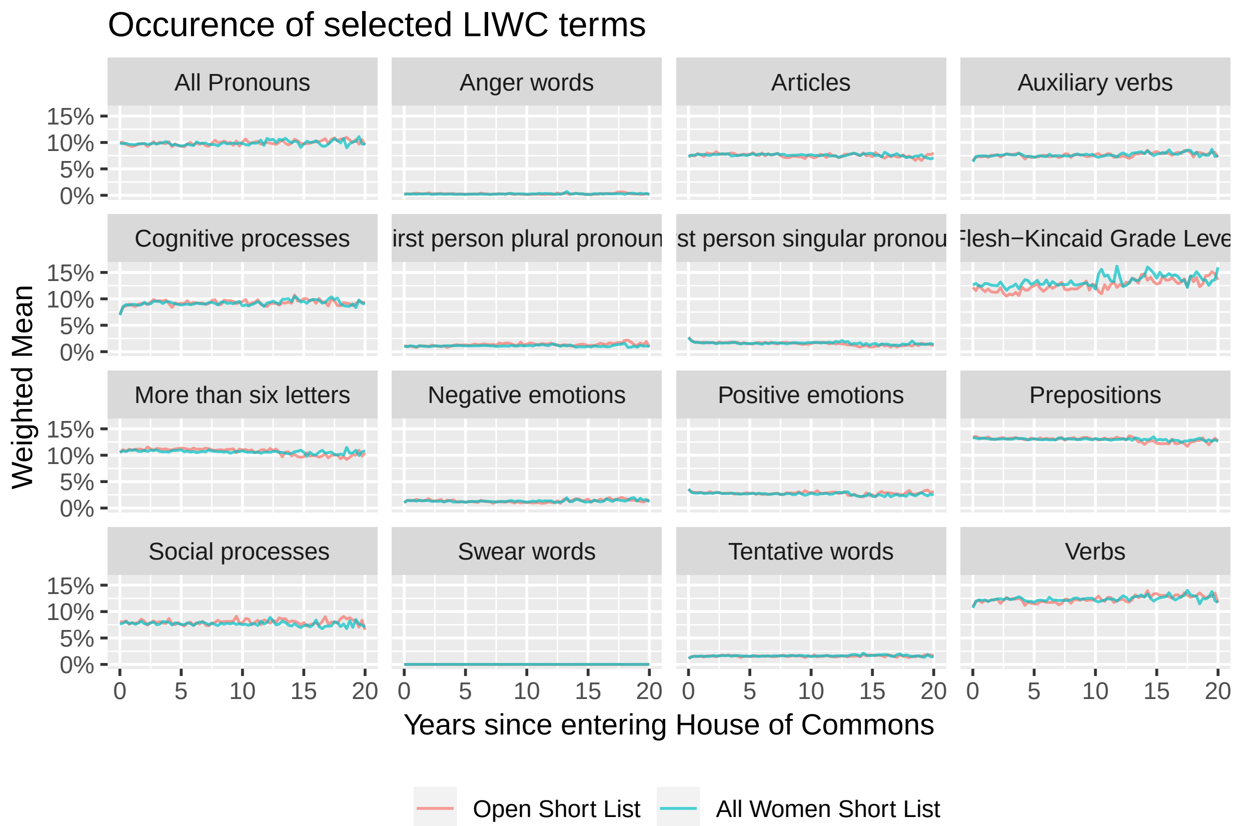

Figure 1: Occurence of selected LIWC terms

There are no categories among female Labour MPs by selection process meeting the |0.2| threshold. Only one category – first person plural pronouns, d=0.19 – exceeded |0.1|.

2.4 Conservatives vs Labour

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

2.5 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).

2.6 POS Analysis

Part-of-speech (POS) tagging was done using `spaCy` (Honnibal & Montani, 2017) and the `spacyr` package (Benoit & Matsuo, 2018). There is one small gender difference ($d = |0.22|$) in the use of plural nouns, which make up 5.85% 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.

Table 4: 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

Table 5: Effect Sizes for All Labour and Conservative MPs

	Labour		Conservatives		Effect Size	
	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Pronouns	10.12	4.87	10.62	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

Table 6: Effect Sizes for Male and Female MPs, All Parties

	Women		Men		Effect Size	
	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Pronouns	10.31	4.65	10.26	4.90	-0.01	negligible
First person singular pronouns	1.99	2.45	2.00	2.52	0.00	negligible
First person plural pronouns	1.11	1.57	1.08	1.59	-0.02	negligible
Verbs	12.88	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

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

	Women		Men		Effect Size	
Word Type	Mean	SD	Mean	SD	Cohen's D	Magnitude
All Nouns	22.18	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

Table 8: 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

2.7 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.

2.7.1 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.

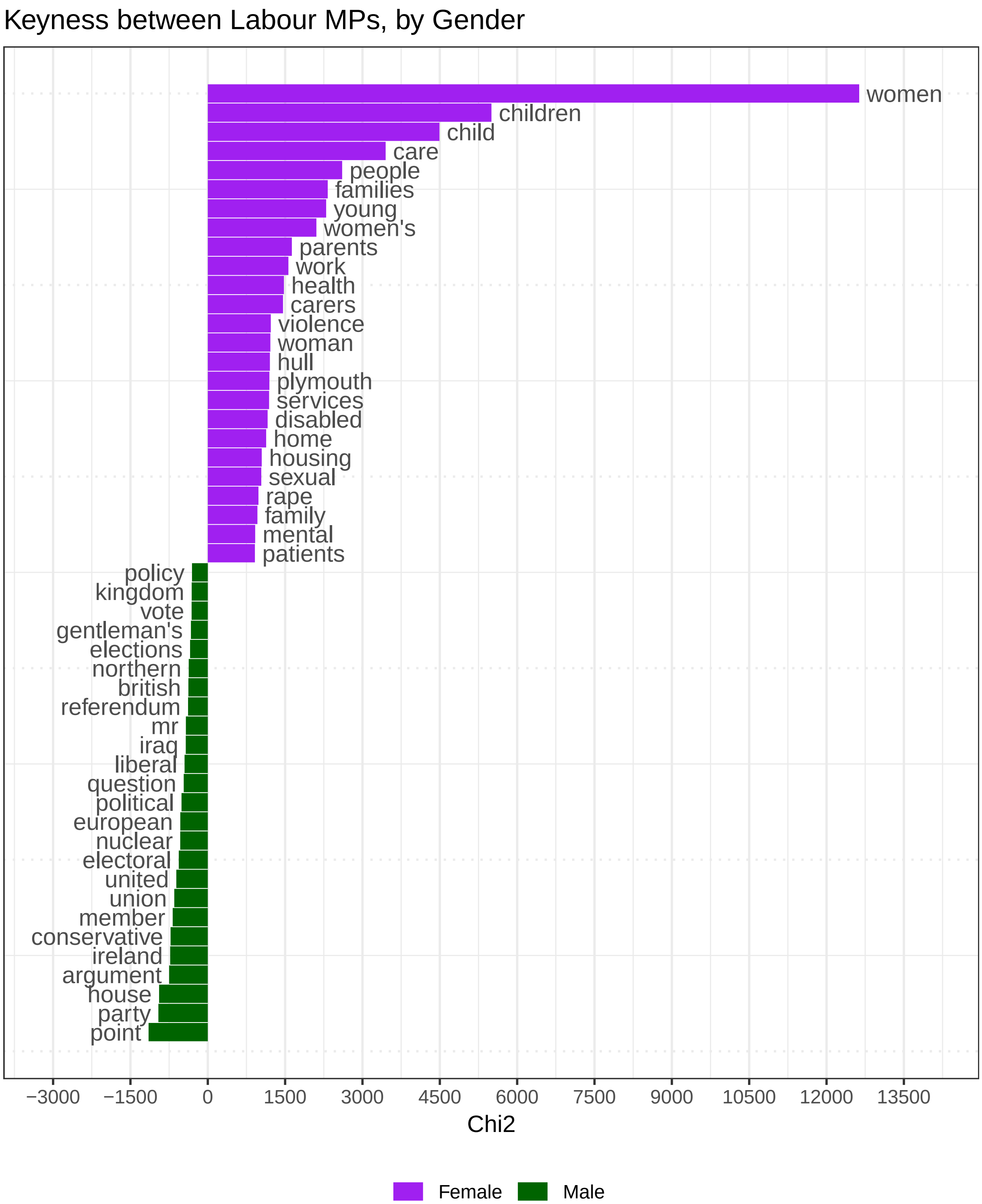

Figure 2: Keyness between Labour MPs, by Gender

2.7.2 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]. 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.

[2]Special Educational Needs

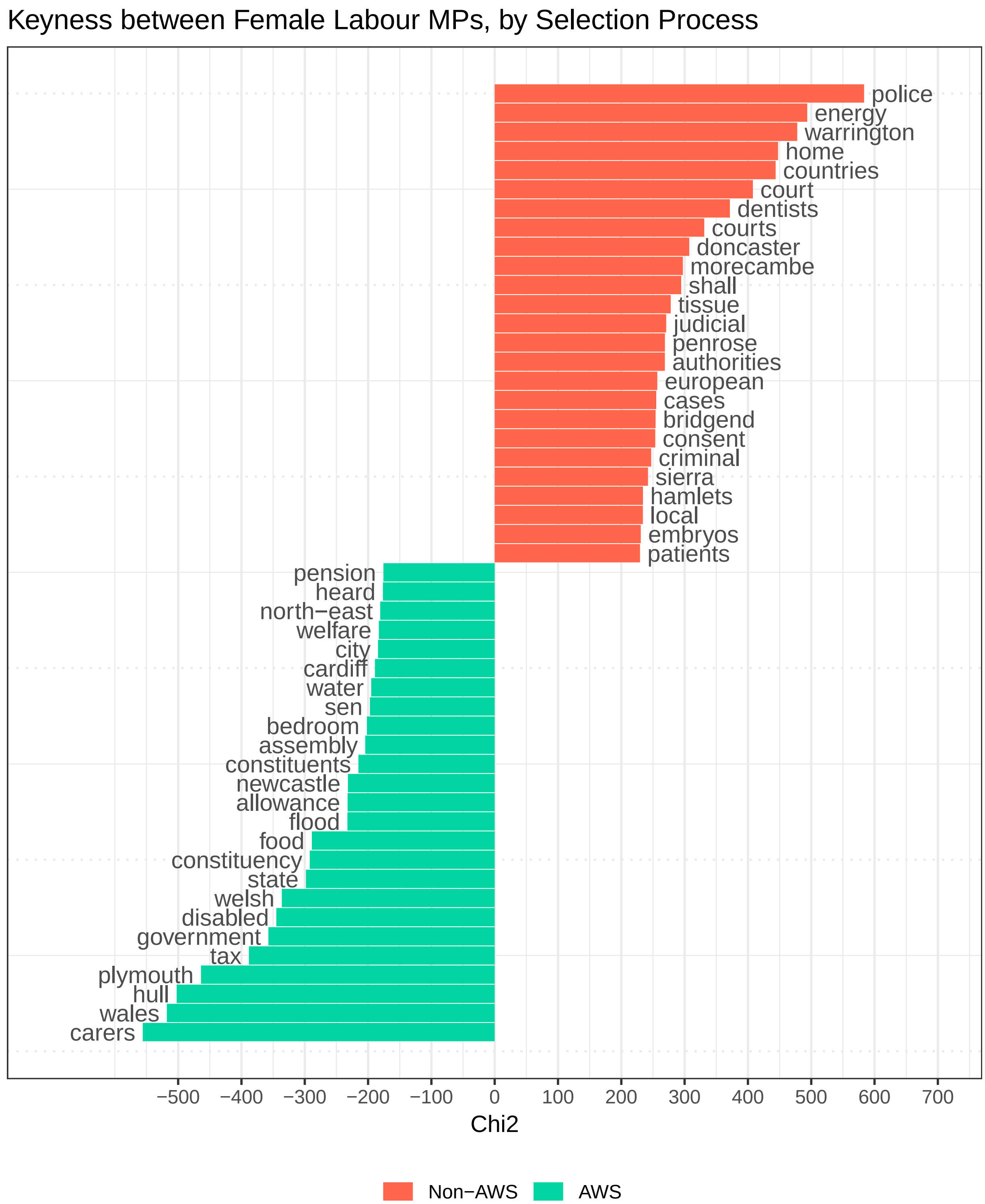

Figure 3: Keyness between Female Labour MPs, by Selection Process

2.7.3 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.

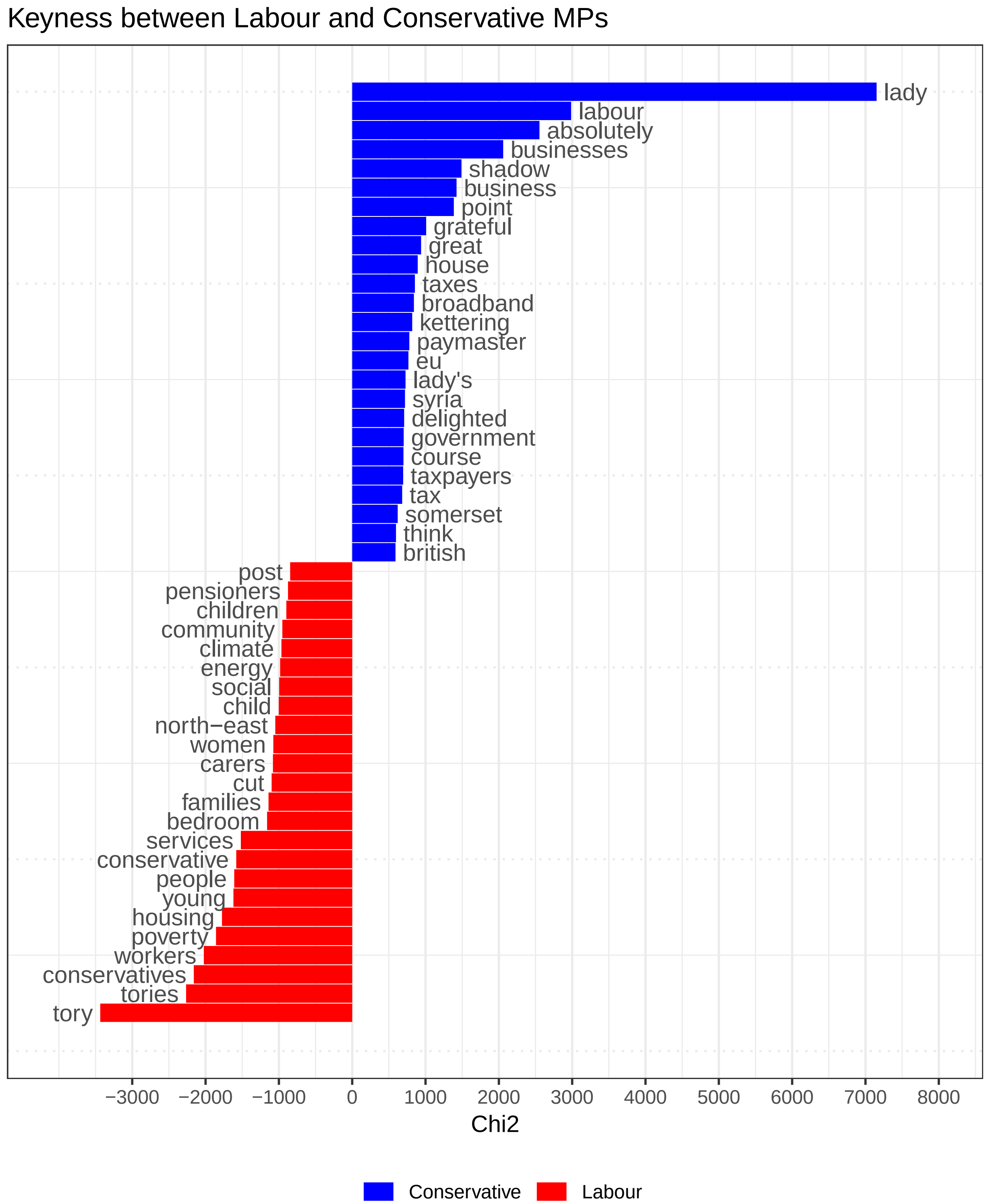

Figure 4: Keyness between Labour and Conservative MPs

2.8 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.

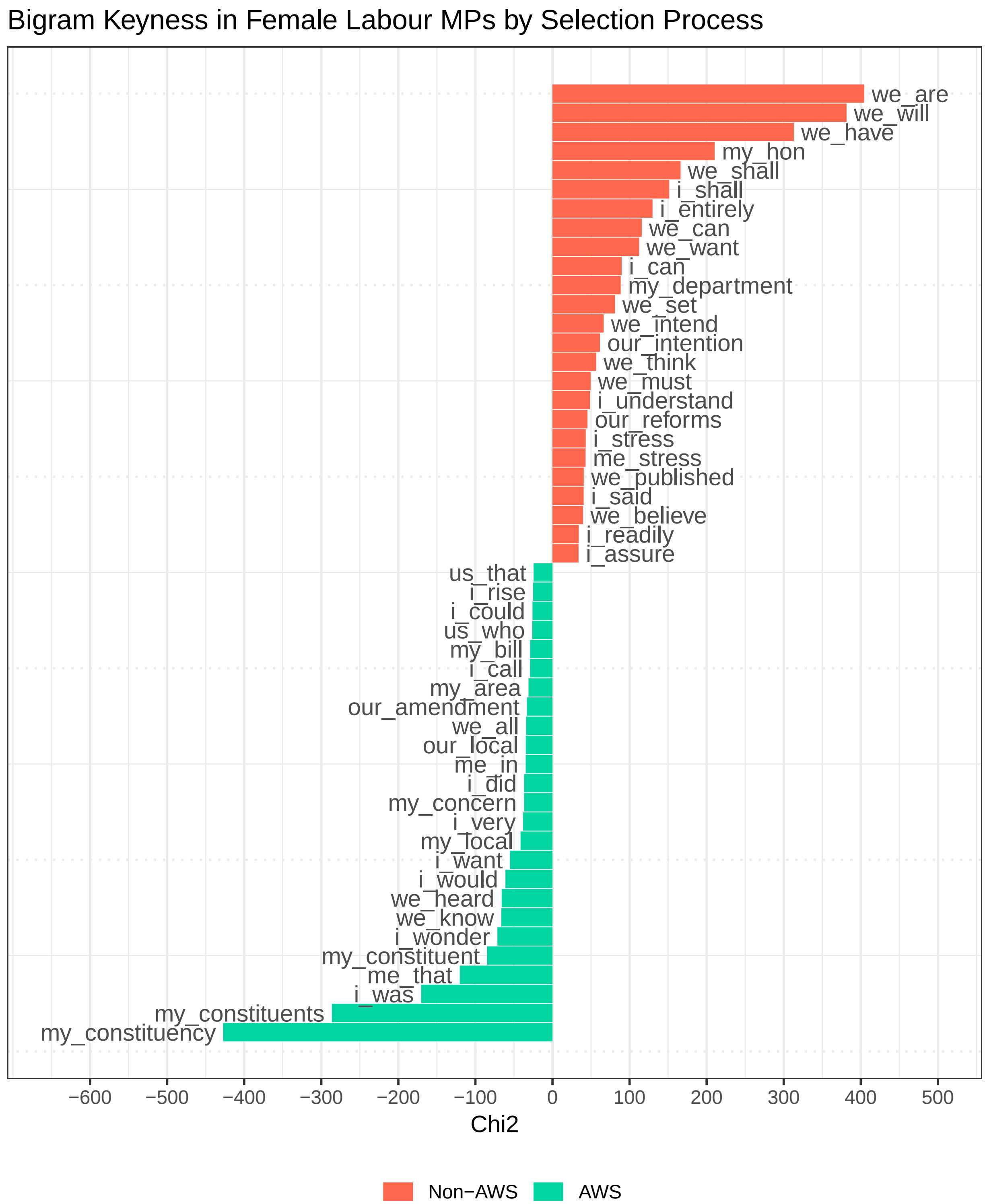

Figure 5: Bigram Keyness in Female Labour MPs by Selection Process

2.9 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.

2.10 Topic Models

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

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

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

We produced two different structured topic model implementations, with different numbers of topics (K).

The first implementation used an algorithm developed by Lee & Mimno (2014), implemented in the `stm` package (Roberts et al., 2018), to estimate the number of topics across all speeches made by female Labour MPs, using the "spectral" method developed by Arora et al. (2013), implemented by Roberts et al. (2018). The resulting topic model has 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 12).

As seen in the word lists in the [appendix][### Short lists vs Non-Short lists - K69], there is relatively scattershot semantic coherence, although exclusivity is high, when using the 69 topic models suggested by Lee and Mimno's (2014) algorithm. We therefore re-ran the analysis, using 30 topic models, which resulted in increased semantic coherence, albeit with slightly lower exclusivity, as illustrated in Figure 7. The lower number of models also makes accurate hand-coding of topics possible.

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

2.10.1 Short lists vs Non-Short lists - K30

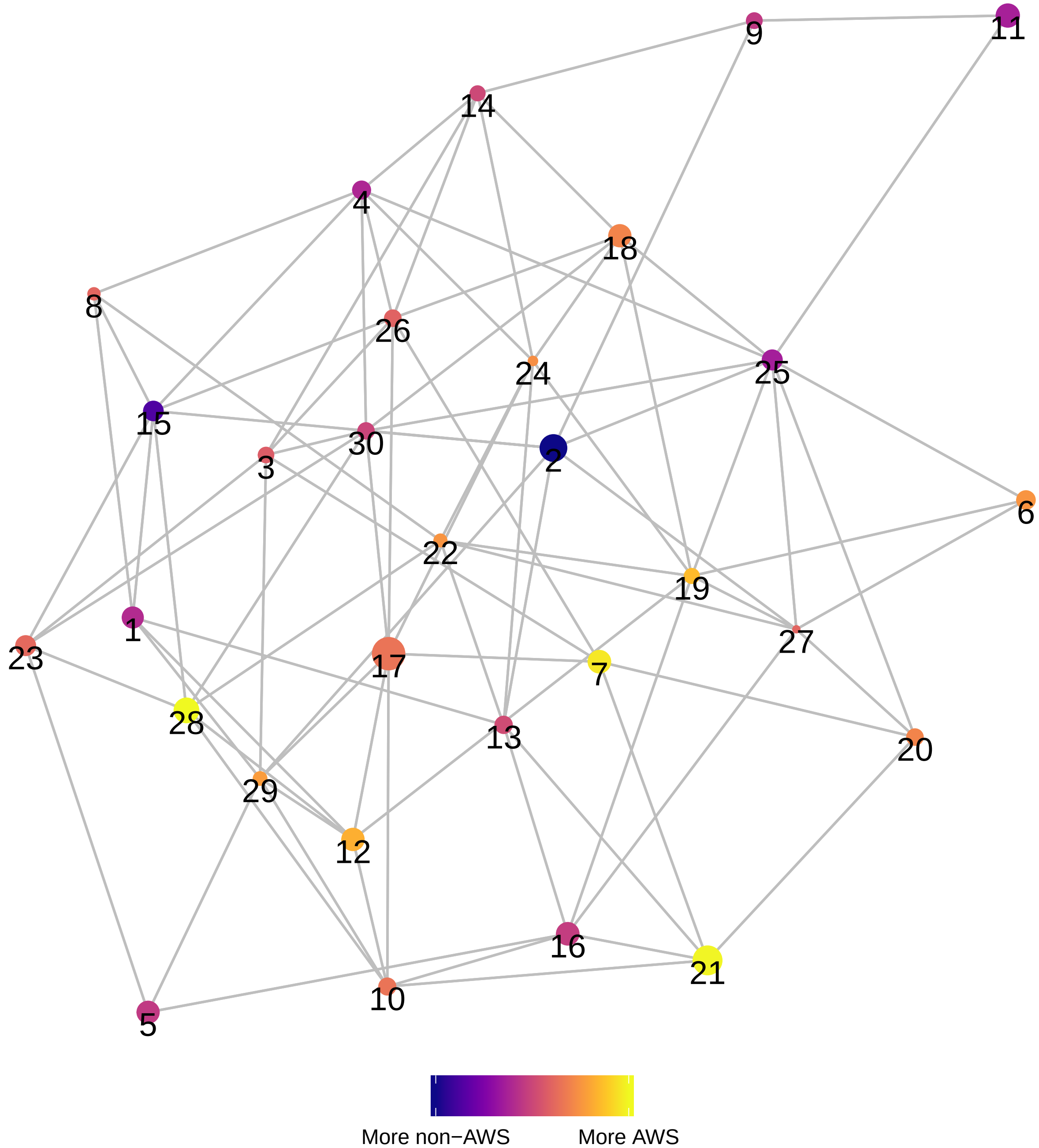

Figure 6: Fruchterman-Reingold plot of K30 Network

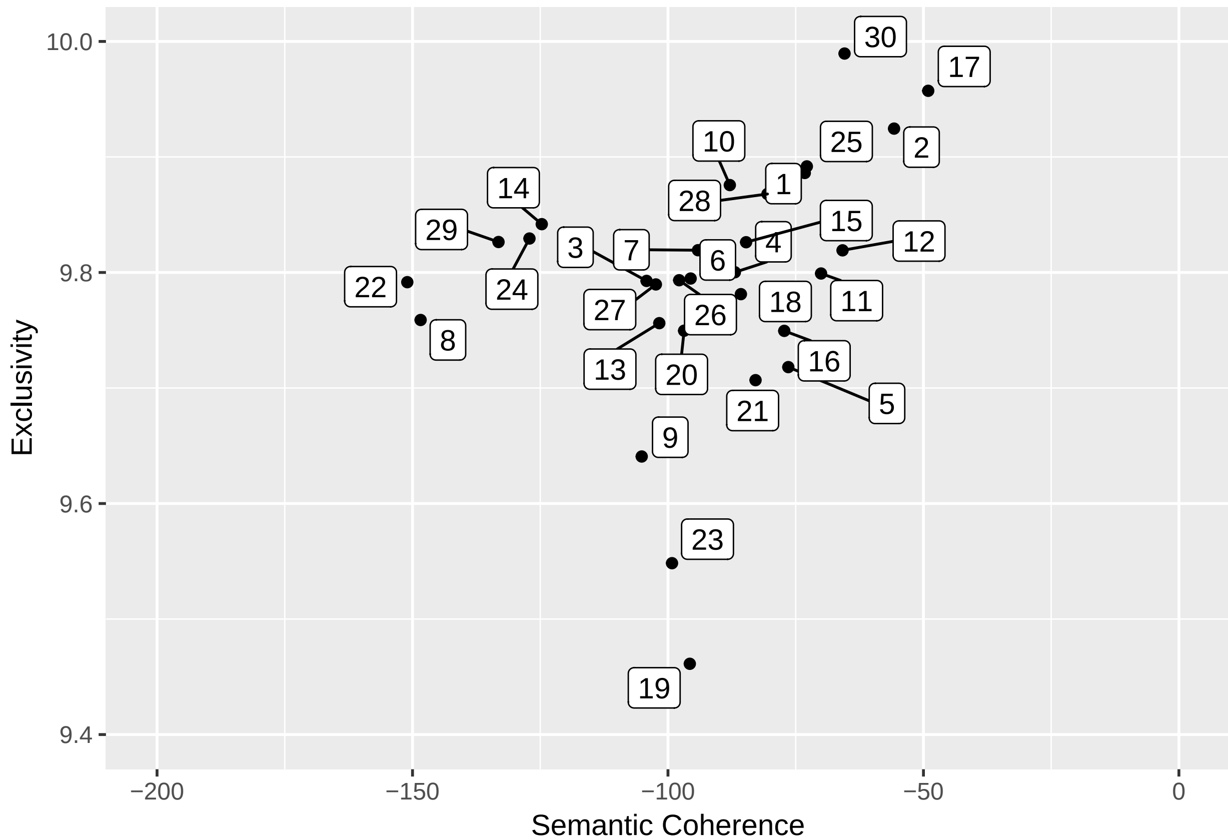

Figure 7: Coherence of K30 Topic Models

Table 9: 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%	11,393	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%	2,193	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%	3,972	2.35%
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%	2,258	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%

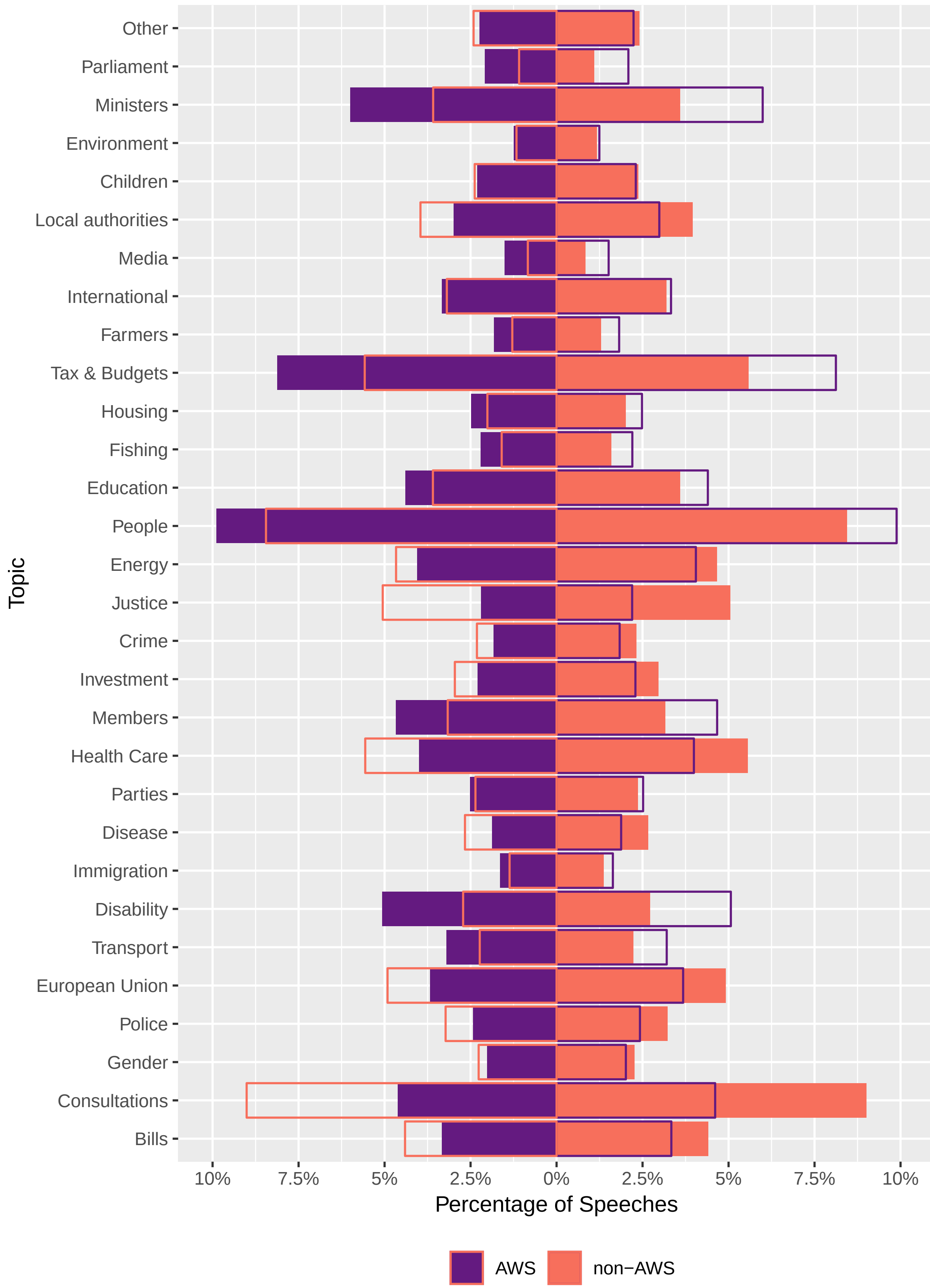

Figure 8: K30 Pyramid Chart

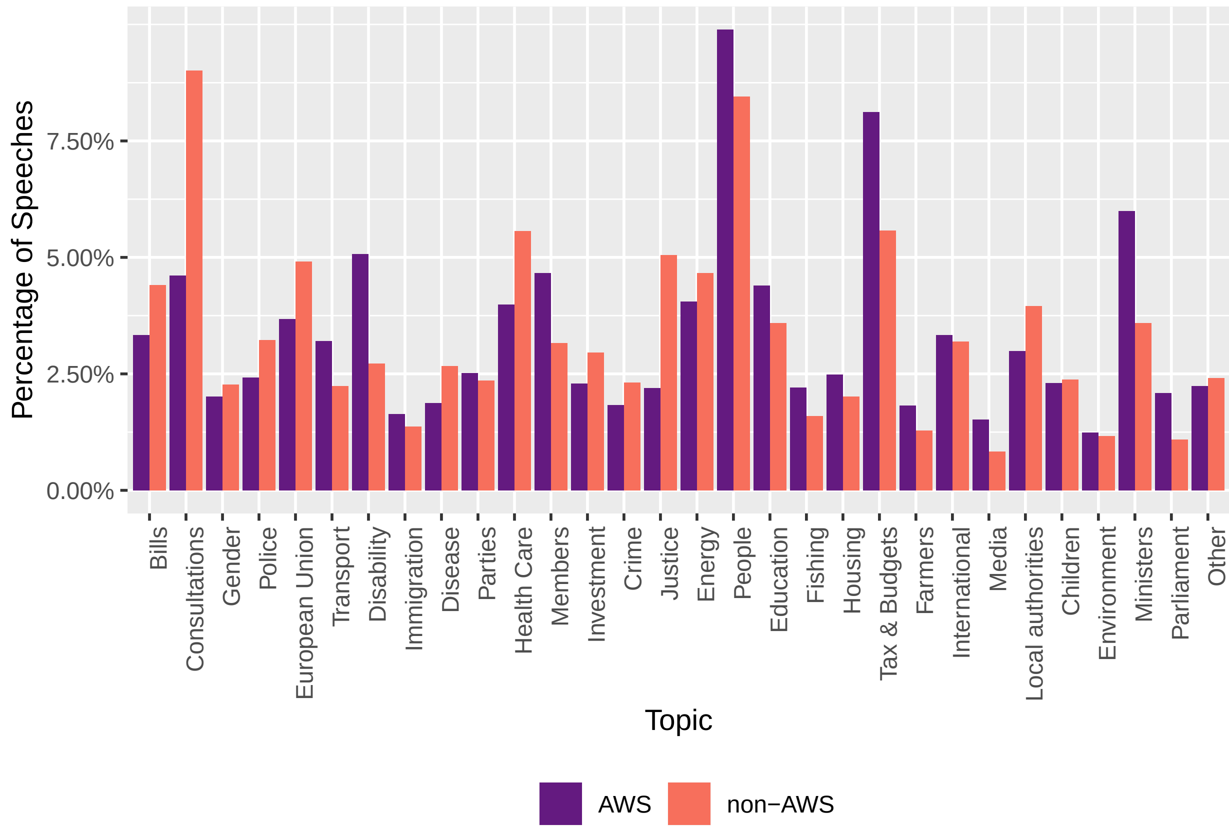

Figure 9: K30 Bar Chart

AWS are – proportionally – more likely than non-AWS MPs are on Topics 29 (parliament), 7 (disability) and 24 (media). They are proportionally less likely to mention Topics 15 (justice), 2 (consultations) and 9 (disease). See 10 for more details. Surprisingly, AWS MPs are slightly less likely to mention gender issues (Topic 3), although the difference is not statistically significant (see the appendix for details).

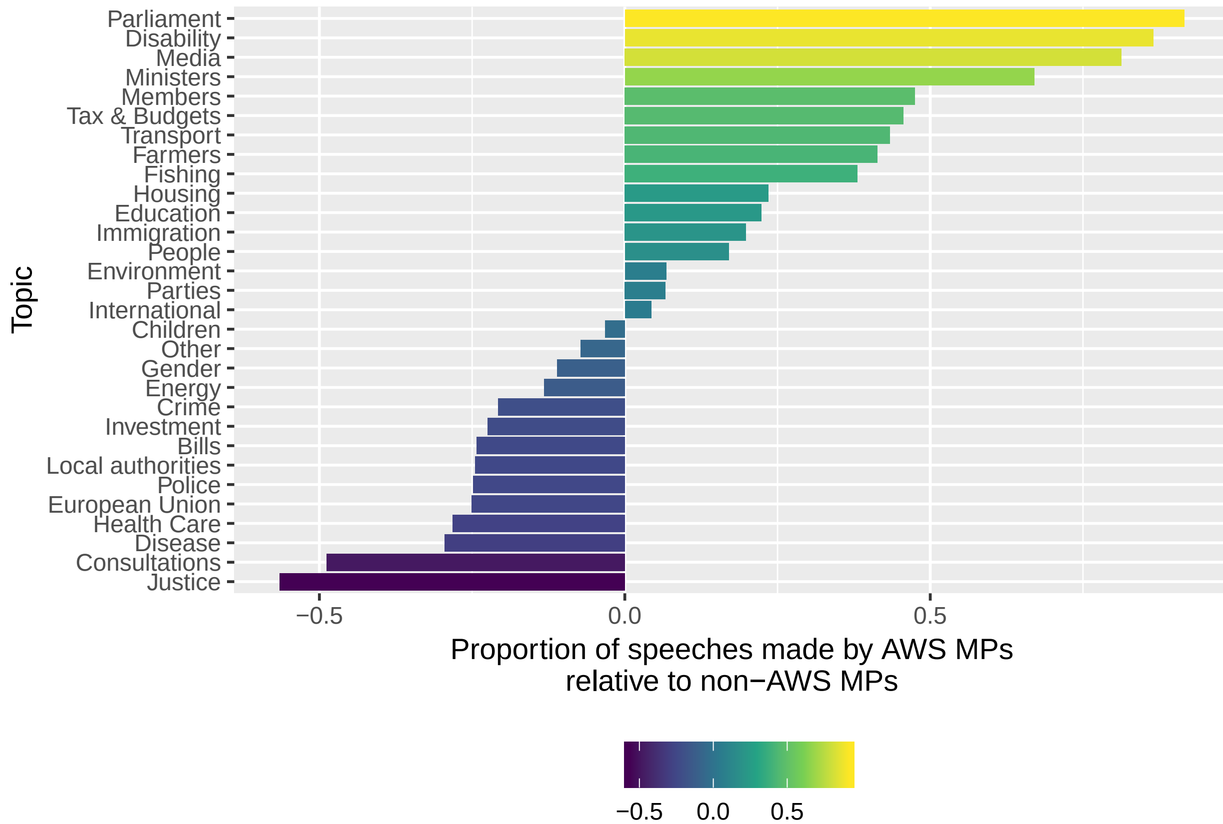

Figure 10: K30 Topic Proportions

2.10.1.1 Word Occurences

Table 10: Words in Topic - K30

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

2.11 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) – the references to their constituents and constituencies suggests AWS MPs shy away from the Burkean concept of trusteeship and see themselves more as strict representatives of their constituents. In Andeweg & Thomassen's (2005) typology of *ex ante*/*ex post* and above/below political representation, AWS MPs lean towards representation "from below", although their selection process is *ex ante*/*ex post*.

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

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

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

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

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

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

3 Appendix

3.1 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, Official, 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
```

3.2 Full topic model estimate summary - K30

```
##
## Call:
```

```
## estimateEffect(formula = 1:30 ~ short_list, stmobj = topic_model_k30,
##     metadata = lab_corpus_fem_stm$meta, uncertainty = "Global")
##
##
## Topic 1:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0449599  0.0006466  69.528 <0.0000000000000002 ***
## short_listTRUE -0.0068573  0.0008049  -8.519 <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)     0.0757526  0.0006139   123.4 <0.0000000000000002 ***
## short_listTRUE -0.0215057  0.0007265   -29.6 <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)     0.0230321  0.0006047   38.09 <0.0000000000000002 ***
## short_listTRUE -0.0007487  0.0006933   -1.08                0.28
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0289246  0.0006492  44.554 <0.0000000000000002 ***
## short_listTRUE -0.0074345  0.0007525  -9.879 <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)     0.0368548  0.0006667  55.280 < 0.0000000000000002 ***
## short_listTRUE -0.0051096  0.0007784  -6.564      0.0000000000525 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
```

```
## Topic 6:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0217914  0.0005743   37.95 < 0.0000000000000002 ***
## short_listTRUE 0.0054471  0.0007683    7.09     0.00000000000135 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0298415  0.0006457   46.22 <0.0000000000000002 ***
## short_listTRUE 0.0131734  0.0007805   16.88 <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)    0.0186102  0.0004835  38.489 <0.0000000000000002 ***
## short_listTRUE 0.0004473  0.0006266   0.714               0.475
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 9:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0249459  0.0005958  41.868 < 0.0000000000000002 ***
## short_listTRUE -0.0050930  0.0007196  -7.078     0.00000000000148 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0378882  0.0004757  79.646 < 0.0000000000000002 ***
## short_listTRUE 0.0020040  0.0005966   3.359             0.000783 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
```

```
## (Intercept)     0.0407968  0.0007000  58.281 <0.0000000000000002 ***
## short_listTRUE -0.0083332  0.0008764  -9.509 <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)    0.0389915  0.0005993   65.07 <0.0000000000000002 ***
## short_listTRUE 0.0082203  0.0007370   11.15 <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)     0.0302229  0.0006158   49.08 < 0.0000000000000002 ***
## short_listTRUE -0.0028501  0.0007829   -3.64             0.000272 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0239299  0.0005277  45.346 < 0.0000000000000002 ***
## short_listTRUE -0.0032117  0.0006350  -5.058          0.000000426 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0409426  0.0006936   59.03 <0.0000000000000002 ***
## short_listTRUE -0.0167370  0.0008408  -19.91 <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)     0.0384150  0.0006632  57.921 < 0.0000000000000002 ***
## short_listTRUE -0.0046137  0.0008730  -5.285          0.000000126 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
##
## Topic 17:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0788616  0.0005743 137.328 < 0.0000000000000002 ***
## short_listTRUE 0.0019859  0.0007189   2.763              0.00574 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0298584  0.0006867  43.480 < 0.0000000000000002 ***
## short_listTRUE 0.0038022  0.0008462   4.493           0.00000702 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 19:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0196099  0.0005022   39.05 <0.0000000000000002 ***
## short_listTRUE 0.0092476  0.0006689   13.82 <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)    0.0204436  0.0005514   37.08 < 0.0000000000000002 ***
## short_listTRUE 0.0038476  0.0007573    5.08          0.000000377 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0460837  0.0008004   57.57 <0.0000000000000002 ***
## short_listTRUE 0.0143005  0.0010136   14.11 <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)    0.0139637  0.0004693  29.753 <0.0000000000000002 ***
## short_listTRUE 0.0055204  0.0005770   9.567 <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)    0.0261611  0.0006760  38.701 <0.0000000000000002 ***
## short_listTRUE 0.0007644  0.0008482   0.901               0.367
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0124096  0.0003989  31.110 <0.0000000000000002 ***
## short_listTRUE 0.0048978  0.0005019   9.758 <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)     0.0426053  0.0006164   69.11 <0.0000000000000002 ***
## short_listTRUE -0.0085872  0.0007437  -11.55 <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)     0.02500711  0.00056428  44.317 <0.0000000000000002 ***
## short_listTRUE -0.00001857  0.00072403  -0.026                0.98
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0149389  0.0004774  31.294 <0.0000000000000002 ***
## short_listTRUE 0.0003278  0.0005898   0.556               0.578
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 28:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0427074  0.0005853   72.97 <0.0000000000000002 ***
## short_listTRUE 0.0145465  0.0007178   20.27 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0187987  0.0005278  35.617 <0.0000000000000002 ***
## short_listTRUE 0.0062975  0.0006934   9.082 <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)     0.0526664  0.0003229 163.079 <0.0000000000000002 ***
## short_listTRUE -0.0037451  0.0003934  -9.519 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

3.3 AWS References to Constituents in Context

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

Table 11: A random sample of KWIC's

Pre	Keyword	Post
. Let me take this opportunity to welcome initiatives in	my constituency	, particularly the Skypad unit , which is based at
pill . Can my right hon . Friend say where	my constituents	can turn now for the justice they ought to receive
that there has been an incredible growth , certainly in	my constituency	, in the number of people having to resort to
During the two years I have been meeting farmers in	my constituency	and making representations to Ministers , many of the issues
	My constituent	Enola Halleron-Clarke , who is 11 years old , suffers
The George Thomas hospice in	my constituency-a	charity named after one of your predecessors , Mr .

broad thrust of the Budget is very bad news for	my constituents	. Hull North will see more individuals out of work
Ratcliffe and Gretton . Yes , as the name of	my constituency	suggests , the largest town is that of Burton upon
but it is of no interest whatsoever to most of	my constituents	, who do not have the time to intellectualise about
like some clarification of how it will affect people in	my constituent's	position . \ n "
has caused widespread and persistent congestion on the roads in	my constituency	. However , the story of Bradford is not unique
it has at St Helier hospital which serves people in	my constituency	. It has , however , been full of praise
Churches in	my constituency	have a link with Lesotho that goes back many years
n " , " I want to set out what	my constituents	would like to happen . First , I will address
effort has failed . This is such an occasion .	My constituent	, Mr . Aranda , first saw me at one
. and hon . Members , I have been encouraging	my constituents	to take advantage of the scheme . Will the Minister
to conclude my remarks . \ n " , "	My constituents	ask me these questions . What happens if Lewisham is
housing ? Will he applaud the initiatives already taken in	my constituency	, and especially in the Vauxhall area , where health
welcome that £ 200 . What advice can he give	my constituents	when faced with high council tax hikes from the Liberal
become more competitive . I have many small businesses in	my constituency	. Since I was elected , they have repeatedly raised
investment in innovators in microgeneration , such as those in	my constituency	, so that people can make genuine choices about fuel
Jobcentre Plus . The Scottish National party Government have excluded	my constituency	from any assistance such as from enterprise zones and the
Have the Government any plans to tackle this and help	my constituents	get on the housing ladder ?
constituency . I have urban areas to the north-east of	my constituency	and a very large rural area running right up to
Allison's chemist in Cockermouth , which is in	my constituency	, provided a very important resource for local people after
supply ? Residents in Sway road , Morriston , in	my constituency	have been threatened with such action because of a fault
been contacted by nearly 50 local police officers living in	my constituency	. Not only are they fearful for their jobs but
described as the end of local democracy . Many of	my constituents	might argue that that has already happened , given that
councils , so will the Secretary of State explain to	my constituents	why county councils are getting additional moneys , but not
, 29 April , and 23 May , but for	my constituents	this may not happen until the process is further down
constituency are viable businesses that benefit the community , and	my constituents	want them to remain so . Will he confirm that
I am really concerned about one of the schools in	my constituency-I	have mentioned it to Ministers before-where only 11 per cent
and secured against their own homes were being quoted to	my constituents	. Was this a condition the council set for the

. Notwithstanding the fact that the track that would benefit	my constituents	lies in her constituency , her constituents would benefit from
, the 37 AONBs , including the Wye valley in	my constituency	, and the Council for the Protection of Rural England
in my constituency . It is the biggest employer in	my constituency	, so it is extremely important to me and my
grateful for this opportunity to pass on the thanks of	my constituents	to the Government for being serious about tackling health inequalities
success since I made my maiden speech on employment in	my constituency	during the debate on the first Queen's Speech under the
a credit to Westminster . \ n " , "	My constituency	gave the world household names such as Pilkington and Beechams
much power just in transmission . As a gentleman in	my constituency	says , it is always either windy , sunny or
paying . They have not met the 4,100 people in	my constituency	who cannot find work-more than a quarter of them are
a new building for the Methodist community in Boothstown in	my constituency	. It will be a genuinely multi-use building . In
Cumbria and near-misses in many other places , including in	my constituency	. We know that the emergency services are providing excellent
coverage of rugby league , which is hugely popular in	my constituency	.
this change in this Bill to ensure that electors in	my constituency	never have to have this terrible experience again .
banks , such as the Brick in the centre of	my constituency	, are lengthening by the day . In the past
, what guarantees can the Secretary of State give to	my constituents	that they will be fully informed of the risks associated
energy companies and changes to the energy company obligation ,	my constituent	may no longer get his hard-to-heat , solid-wall home insulated
\ n " , " No sense of understanding of	my constituent's	position was given in that final paragraph . The CSA
, it looked at Barton Hill , an estate in	my constituency	that is in a ward ranked 133rd on the national
Trafford , which has a Conservative council and is where	my constituency	is located . We are seeing a twin squeeze ,
world . It is a particular issue for many of	my constituents	, and the violence and human rights abuses have spanned
bandied around-because I want to talk about the reality that	my constituency	faces . Our health and social provision has developed into
of life and death . \ n " , "	My constituent	Royston Brett set off on Friday and has cycled almost
to some people than to others . For people in	my constituency	, the Government's changes so far have resulted in a
Bill on social care , if the Minister thinks that	my constituents	are happy with the package we have before us at
Alstom Power , a company that makes gas turbines in	my constituency	, has taken up the challenge . At its conference
Chamber , I have been contacted by a number of	my constituents	who are concerned about the Bill and would rather see
again have a university . However , Nene college in	my constituency	hopes to change all that , and I support strongly
That is the right way forward . Each person in	my constituency	gets £ 7 less than in the neighbouring constituency of

, but those have not materialised , leaving women in	my constituency	and many others across the UK facing hardship , stress
in this debate , which is of great importance to	my constituency	. I wish to draw in particular from the circumstances
I have been making complaints on behalf of	my constituents	for some time about the poor performance of rail services
interest that I wish to raise . A number of	my constituents	are families bereaved as a result of the Hillsborough disaster
, which have already proved important in creating jobs in	my constituency	. Is he aware that many employers , including those
I have described , and frustration on the part of	my constituent	, we received the letter dated 18 September that I
women . If the services were moved , some of	my constituents	simply could not access them as they should . \
health problems ? Will he look into the case of	my constituent	, Mrs . Jenkins , whose disability living allowance was
hope I will soon be in a position to reassure	my constituents	that much-needed investment in Lewisham homes will be forthcoming .
to say that we have some of that excellence in	my constituency	, with companies such as Baxi Potterton , Aircelle ,
. Mullin) . This is a big issue in	my constituency	, where inappropriate development on garden sites is taking place
west coast services that link Bangor and Llandudno , in	my constituency	, to London . As a regular user , and
and Sir Malcolm Thornton . All have represented part of	my constituency	and all left this House on 20 April or 1
When I met	my constituents	in Highway ward on Saturday , they told me that
can make a clear distinction between the two . In	my constituency	, one thing of which I am most proud is
matter of great importance to the people of Merseyside and	my constituents	, even though it relates to the South Yorkshire police
prison . An ombudsman's inquiry takes time and , as	my constituent	says , time is not on his side . In
they spend their money . \ n " , "	My constituency	has a close relationship with the textiles industry . Recently
The outcome of the consultations , e-consultations and debates around	my constituency	was finely balanced . A small majority felt that there
institutions , customers and members , but just as all	my constituents	stand to gain from the contribution that the Bill can
not sure whether that is correct because several hundred of	my constituents	write to me regularly . For example , Carrie Flint
Over the weekend , 400 job losses were announced in	my constituency	, with the closure of the Stampworks in Ayr ,
many communities because 12 of the 48 post offices in	my constituency	are proposed for closure . The Government recognise the social
which was only yesterday . I sent a response from	my constituency	. I can hope only that it had some influence
39 of the Crown post offices , including Lancaster in	my constituency-and	the relationship MPs have with Post Office Ltd ? Many
' Bills were introduced on this issue , one by	my constituency	neighbour , my hon . Friend the Member for Brigg

expensive failure ? It has been a cost-effective success in	my constituency	.
already taken several interventions . \ n " , "	My constituent	was in work and owned his own home , and
services , for the time that he took to greet	my constituents	and for the care and the honesty with which he
remain extremely important employers in Burton upon Trent , in	my constituency	. There has been a gradual decline in the number
legacy of BSE and , in the northern area of	my constituency	, cattle testing positive for TB , which is a
of the problems , and one issue that some of	my constituents	have raised is that written reports from their doctors or
by the necessary funding arrangements , so that families in	my constituency	will see the materialisation of extra child care places that
In	my constituency	we obviously welcome the two new aircraft carriers and the
everything will be fine . \ n " , "	My constituent	Joe-one of the many people I talked to in the
pooh-poohing of the Bevan Foundation's inquiry and report , but	my constituency	took part in that inquiry and I did not see
how important the review of children's heart surgery is for	my constituents	, as it is for those of each of the
she work with other Departments , so that pensioners in	my constituency	and elsewhere can have good , warm housing , a
certainly not going to provide for as many people in	my constituency	as EMA did . Although Conservative Members can talk about
is perhaps because I have a truly magnificent cathedral in	my constituency	that is over 1,000 years old that I feel strongly
, but it is an issue of real importance to	my constituency	. \ n " , " Cockenzie's coal-fired power station
tax will cost our local economy £ 1.9 million in	my constituency	and almost twice that in Salford , because tenants will
to deliver solar panels on public and community buildings in	my constituency	. It told me , in relation to the cut
" Many of	my constituents	who work in the probation service have written to me
she aware of very similar problems at Samworth Brothers in	my constituency	? Long-serving workers are seeing their night shift and weekend
\ n " , " Many small business people in	my constituency	are struggling to stay afloat , particularly in the face
, but I can tell the hon . Gentleman that	my constituents	do not see it as fair . \ n "
he aware that although PEP is available to some of	my constituents	in Hove and Portslade , it is unfortunately not available
a year . I know that many such people in	my constituency	will not get any benefit afterwards because they will probably
only language I speak fluently is English . But in	my constituency	in the city of Bristol , 91 different languages are
local licensing schemes , because in my experience , in	my constituency	, people want more regulation , not less ?

sympathise with the anxieties of people in Ruislip-Northwood , but	my constituents	in north Paddington very warmly welcome the decision on the
Adjournment debate , I would like to pay tribute to	my constituent	Nicola Braniff , the partner of the late Stephen O'Malley
throughout the constituency . I will strive to serve all	my constituents	to the best of my ability . \ n "
agree with the sentiment . \ n " , "	My constituent	continues : \ n " , " " I could
to present this petition on UK aid on behalf of	my constituents	. The signatures were \ n " , " gathered
that organisations such as Rucksack and other small charities in	my constituency	, such as Harbour Place , will say that they
, much to my disappointment and the huge disappointment of	my constituency	and borough , which had the second-largest vote in the
next to impossible , as there is no way for	my constituents	to contact Concentrix . The HMRC has a hotline for
for that helpful reply . Does she appreciate that in	my constituency	, during a period of about a year , two
we need for our industry . We are lucky in	my constituency	to have rail and the M4 , which means that
I believe that	my constituency	contains more BNP councillors than any other constituency in the
I was-at Calderhead school in Shotts , which is still	my constituency	. I clearly recall that , when I asked those
havoc they wreak on estates in my constituency , and	my constituency	is not an exception . If we are serious about
consumer protection Bill , which will provide important safeguards for	my constituents	. People in Northampton carry high levels of credit .
In	my constituency	, long-term unemployment has increased by almost 600 % in
Many of	my constituents	will have been deeply concerned by the admission of Peter
up and take part in this debate and to answer	my constituents	' questions . I have something of interest to tell
to young girls , many of whom are born in	my constituency	. It is totally unacceptable that the human rights of
to happen . \ n " , " People in	my constituency	have looked at the range of care that needs to
the specific case-which I can refer to him-of one of	my constituents	who was bankrupted after a VAT inquiry ?
I want to share with the House one anecdote from	my constituency	. When I was campaigning and canvassing in the general
time to debate miscarriages of justice ? Last night ,	my constituent	, Mr . Michael O'Brien , accepted £ 300,000 in
, as others have pointed out this morning . In	my constituency	, there is a significant problem with assaults in the
, Sue Essex , has been a huge success .	My constituents	have told me that it has enabled many of them
make such a major difference at the north end of	my constituency	.
Does he agree , however , that the lives of	my constituents	and many others are blighted by these trees , and

As well as big universities such as the ones in	my constituency	, I am concerned about smaller universities , which often
that was going into the eco-village in Weardale , in	my constituency	? That would have created many green jobs in an
insurance industry . What is she going to say to	my constituents	?
the affected areas of need . The Weaver ward in	my constituency	is part of the Staffordshire-Derbyshire objective 5b area , demonstrating
On 6 December ,	my constituent	, Kabba Kamara , was tragically stabbed to death while
. \ n " , " Like many others ,	my constituency	is one of great contrasts , from the leafy streets
. We are on the west coast main line .	My constituency	contains four rail stations , three of which are on
Mary Stevens hospice in Stourbridge is much loved by all	my constituents-so	much so that it derives 82 per cent . of
to the most vulnerable consumers . Many of those in	my constituency	are forced to use expensive prepayment cards ; what is
the Minister for Pensions Reform for meeting me to discuss	my constituents	’ case . I hope that amendments to the Bill
n " , " Let me highlight three examples from	my constituency	caseload that illustrate the vulnerability of many people who have
constituents . It is probably the most important issue in	my constituency	, and has been for a considerable time . It
clients , people seeking debt advice in East Lothian ,	my constituency	, are now saddled with average payday loan debts of
who was concerned about the level of CCTV coverage in	my constituency	. That speaks volumes when we take into account the
framework for protection from discrimination has been won , and	my constituents	have shown consistent support for such measures . I congratulate
standards officers are aware of many similar examples . In	my constituency	of Luton , South , scare tactics are used to
and guns . \ " \ n " , "	My constituent	went on to tell me that he had discovered on
Is my right hon . Friend aware that many of	my constituents	would like to buy British products in recognition of the
many of the early asbestosis claims from Hebden Bridge in	my constituency	might not have succeeded under the proposed 75 per cent
At least nine members of the PRS are based in	my constituency	, and the wider south-west is blessed with prolific and
that is not regulated properly , with the result that	my constituents	, who have small sums of money available to invest
my constituency will get a welcome and much-needed boost .	My constituency	includes Whitchurch comprehensive school , the biggest comprehensive school in
In 2010 , I had three jobcentres in	my constituency	. Old Swan was closed by the Minister’s Department at
	My constituent	, Richard Belmar , has now spent nearly three years
on our streets . \ n " , " In	my constituency	those officers are declining in number , yet the area
Two of	my constituents	, Jeanette Macleod and Margaret Prior , have both received

go ahead . There is huge concern about this in	my constituency	and across the north . Was the Prime Minister told
a commitment would be warmly welcomed by Corus workers in	my constituency	and elsewhere in the UK .
know they are all feeling the pain . Unemployment in	my constituency	has jumped by 16.2 % . We now have the
ago , I visited XLP , a charity based in	my constituency	and operating across London to tackle gangs and violent youth
should have such a centre in Northampton , so that	my constituents	can get proper access to justice to help them with
the moment . \ n " , " People in	my constituency	tell me that their biggest concerns are about jobs .
capital developments are either planned or already in progress .	My constituents	are really seeing the benefits of massive investment in the
to consider how the regulator is responding to requests from	my constituents	, who have to wait until the gas supplier receives
nearly two decades without being able to contact them .	My constituent	is in litigation against the police , and feels a
at hand . Given the high level of interest in	my constituency	, I recently held a listening event that was kindly
Wilberforce Freedom fair trade coffee , which is produced in	my constituency	of Hull , so there are commemorative projects of that
" , " bring to her attention the situation of	my constituent	George Rolph , who is currently on the 23rd day
London , with nearly 13 people chasing every job in	my constituency	. As a result of the cuts in the public
. Would he like to visit the children's centres in	my constituency	that have no children ?
long-term unemployment has gone up . More and more of	my constituents	are dependent on food banks that operate in my constituency
care that they deserve , particularly during difficult times .	My constituents	will welcome the Bill for its clarity and fairness .
" A major supermarket is opening in Cefn Mawr in	my constituency	next Monday , and I welcome that . I welcome
for schools . \ " The outcome was that in	my constituency	and in many areas like it , 30 % of
for the people of Welwyn Hatfield , but I know	my constituents	sent me here to win them more jobs , bring
not a problem for me or for the people in	my constituency	. In fact , they would probably like to see
another young boy has been tragically stabbed to death in	my constituency	. Myron , a talented young rapper , was well
to invigorate the UK and radically transform east London and	my constituency	, which I am honoured to serve . As with
that a large number of hard-working , two-income families in	my constituency	will be particularly badly hit by any move from a
work force . \ n " , " Thankfully for	my constituents	as customers of the postal system , those differences have
Loaves and Fishes food and bank in Easington Lane in	my constituency	. It opened last September and is one of many
, which works hand in hand with the police in	my constituency	?

my primary care trust in north-east Derbyshire and dentists in	my constituency	to find a local solution . These reforms coincide with
ago . It will come as a huge relief to	my constituents	, who all express the view not only that this
hon . Members , with the motorcycle industry and with	my constituents	. My hon . Friend the Member for Rhondda introduced
heartening thing about spending time with PCSOs-as I did in	my constituency	on Friday-is the number of people who know their names
can be used to improve the job opportunities available to	my constituents	. \ n " , " Burnley is a mere
trade with Europe , and the thousands of people in	my constituency	who have found work through the support of the European
years ago there was massive under-enumeration of the population in	my constituency	and my borough of Westminster , as well as in
massive part of the cost of living for many of	my constituents	. \ n " , " Last week in my
and communities . I know that only too well from	my constituency	of Wigan . \ n " , " Although I
on salaries of over £ 150,000 . I think that	my constituents	will see the tax as a just tax , and
investment , the result of which can be seen throughout	my constituency	through the renewal of children's play areas , the relaying
the local force polices , and although vehicle crime in	my constituency	has increased over the past year , it has reduced
tried to follow up on the Prime Minister's pledge to	my constituents	, his officials said that no help was forthcoming .
ready for implementation . It will also delight thousands of	my constituents	who have raised with me the threat of climate change
has its main offices in Swansea , where many of	my constituents	work . Why on earth we are here again ,
in the country . Mr Ash Naghani , one of	my constituents	, told a local newspaper : \ n " ,
would do for the 4,000 people who are unemployed in	my constituency	of Leeds West . \ n " , " One
reductions in incomes to ordinary people in benefits . In	my constituency	the average working-age adult is losing £ 560 per year
inequalities . \ n " , " Two wards in	my constituency	have high numbers of people caring for people with stroke
seriously , and their perpetrators must be punished properly .	My constituents	and I certainly do not want to see a 50
to rise to my feet again . In Hackney in	my constituency	, we have a new city academy , to which
improve such measures as are in place to ensure that	my constituents	benefit as much as possible from the meagre offering they
One of	my constituents	recently had his adoption allowance cut because his child received
out whether the issues that dominate in those areas of	my constituency	that have most need , most crime and most deprivation
n " , " One of the ceramics companies in	my constituency	, Naylor , is a family company , not foreign-owned
, such as those at Mount Pleasant sorting office in	my constituency	, are protected ?

is certainly one reason why the measure is popular in	my constituency	and elsewhere . The Tories turned the welfare state into
is under threat of being withdrawn-a very important issue for	my constituents	. \ n " , " The petition states that
hear that life expectancy in the more deprived parts of	my constituency	is lower than the life expectancy of people living in
particular constituency issue-the big threat to the Llanishen reservoir in	my constituency	, and the threat to Cardiff as a whole .
be at different schools , miles apart . Many of	my constituents	do not have cars , so it can be almost
a well attended housing information event in my constituency ?	My constituents	were engaged in it , and were interested to learn
I shall vote for certainty and a better deal for	my constituents	. \ n "
Dundee West (Jim McGovern) , a number of	my constituents	have been on the employment and support programme for two
aware that , during the summer recess , Honda in	my constituency	announced another 700 jobs to manufacture the new Civic ?
pleased to have secured this important debate on behalf of	my constituents	in Cumnock and Girvan . I will shortly present to

3.3.1 Short lists vs Non-Short lists - K69

The first implementation used an algorithm developed by Lee & Mimno (2014), implemented in the `stm` package (Roberts et al., 2018), to estimate the number of topics across all speeches made by female Labour MPs, using the "spectral" method developed by Arora et al. (2013), implemented by Roberts et al. (2018). The resulting topic model has 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 12).

There are several clusters of topics in 11. 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.

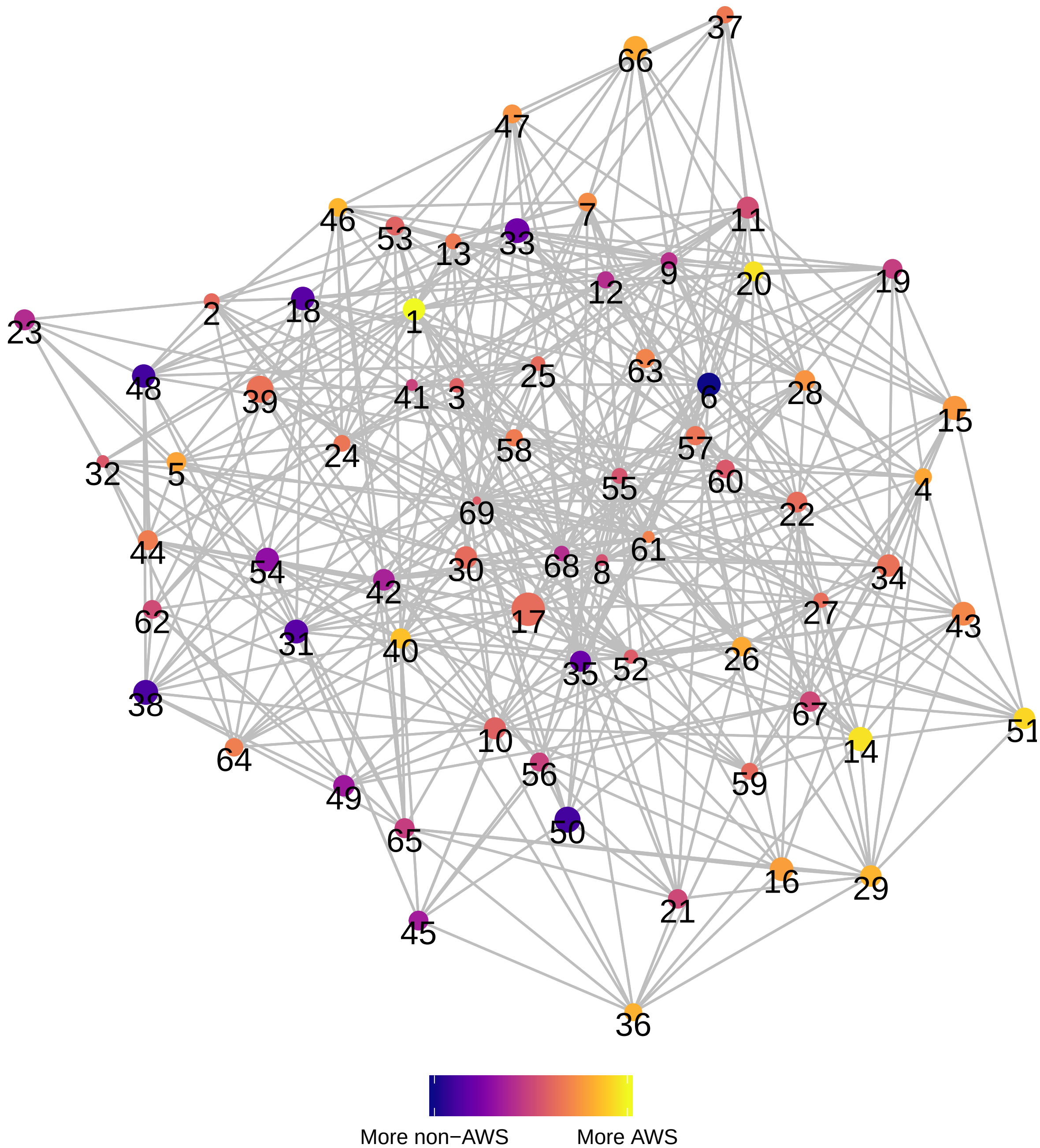

Figure 11: Fruchterman-Reingold plot of K69 Network

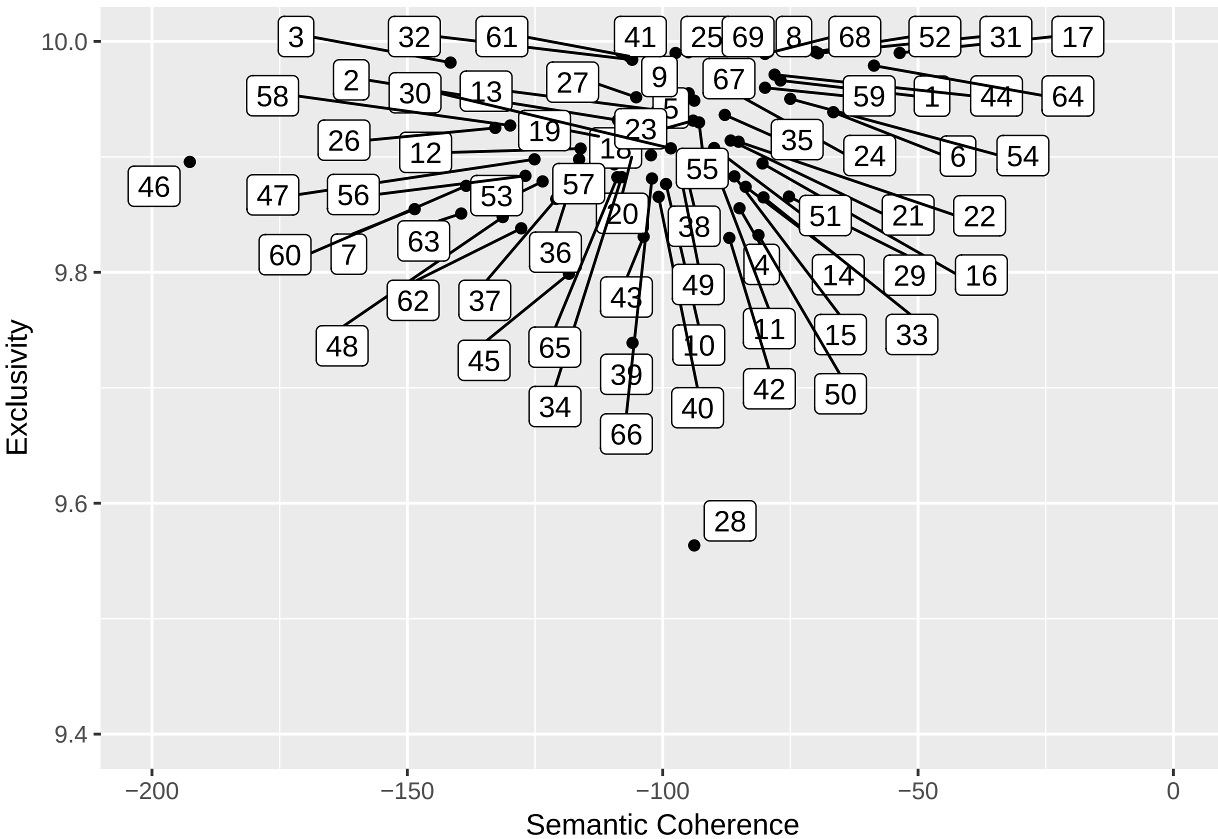

Figure 12: Coherence of K69 Topic Models

Table 12: 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%

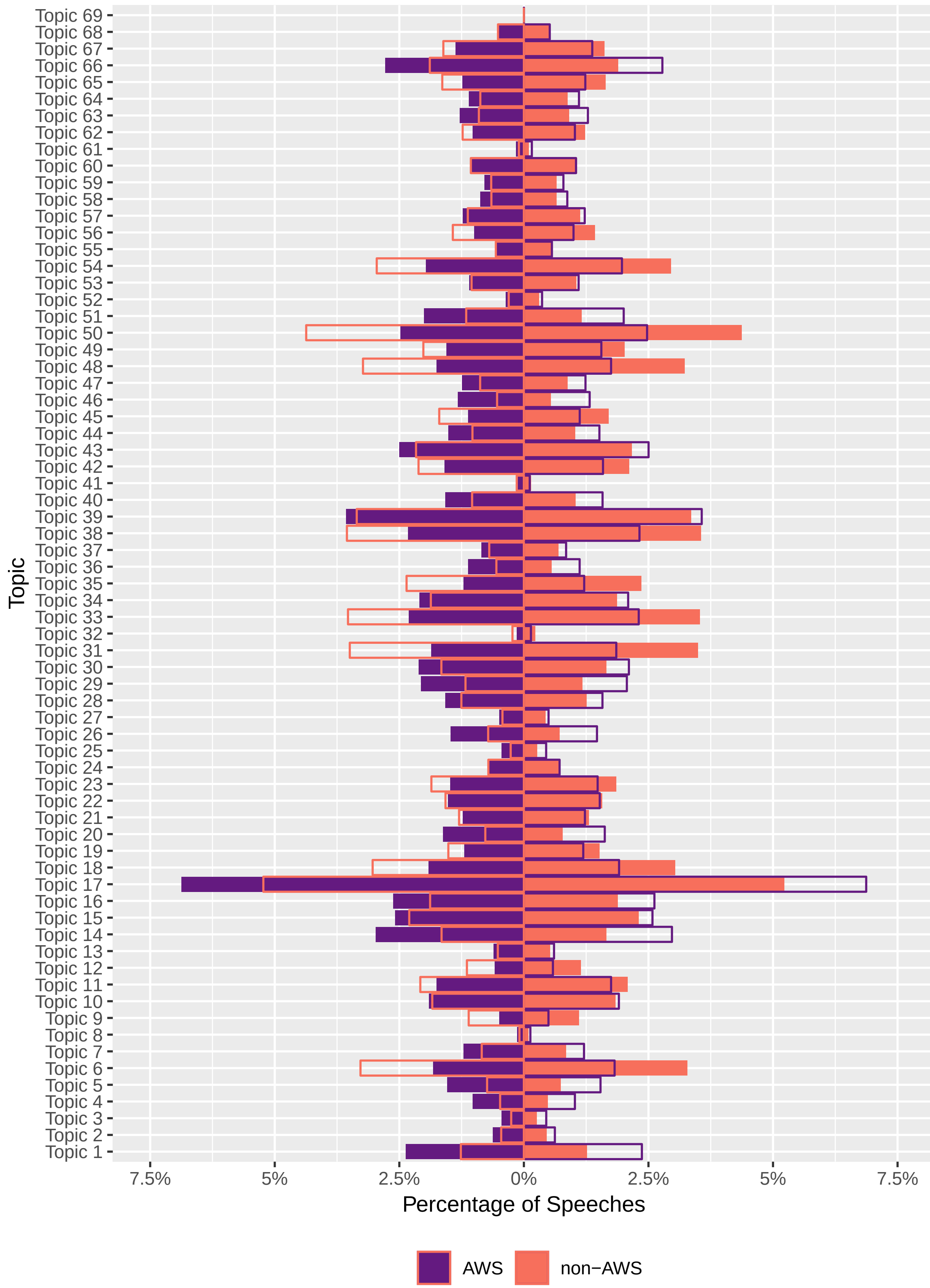

Figure 13: K69 Pyramid Chart

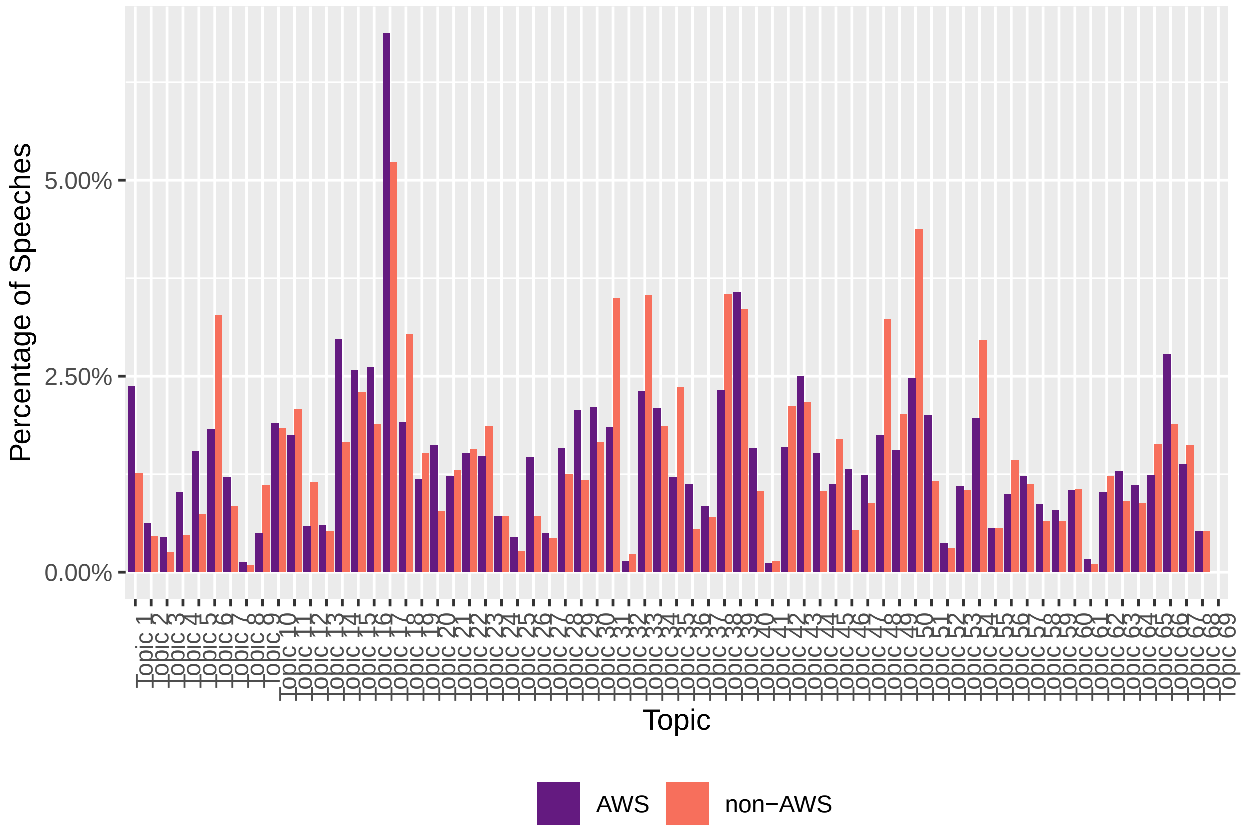

Figure 14: K69 Bar Chart

3.3.1.1 Word Occurences

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

Table 13: Words in topic - K69

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

3.4 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, stalkin
```

```
##       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, @nhcons
##       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
```

3.5 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)    0.0170435  0.0002879   59.20 <0.0000000000000002 ***
## short_listTRUE 0.0069026  0.0003496   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)    0.0058955  0.0002420  24.358 <0.0000000000000002 ***
## short_listTRUE 0.0007062  0.0003050   2.315              0.0206 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0087144  0.0001127  77.309 <0.0000000000000002 ***
## short_listTRUE 0.0002131  0.0001475   1.445               0.148
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0064743  0.0003071   21.08 <0.0000000000000002 ***
## short_listTRUE 0.0036202  0.0003918    9.24 <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)    0.0120624  0.0002519   47.88 <0.0000000000000002 ***
## short_listTRUE 0.0035421  0.0003303   10.72 <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)     0.0313831  0.0004291   73.14 <0.0000000000000002 ***
## short_listTRUE -0.0093831  0.0004957  -18.93 <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)    0.0081985  0.0003833  21.390 < 0.0000000000000002 ***
## short_listTRUE 0.0024229  0.0004801   5.047           0.00000045 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 8:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0155977  0.0001354 115.222 < 0.0000000000000002 ***
## short_listTRUE -0.0006674  0.0001470  -4.542           0.00000559 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 9:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0106919  0.0002692  39.718 < 0.0000000000000002 ***
## short_listTRUE -0.0025219  0.0003483  -7.241     0.00000000000045 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0147989  0.0004500  32.885 <0.0000000000000002 ***
## short_listTRUE 0.0002626  0.0005572   0.471               0.637
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
```

```
##                  Estimate Std. Error t value           Pr(>|t|)
## (Intercept)     0.0131078  0.0004357  30.084 <0.0000000000000002 ***
## short_listTRUE -0.0009014  0.0005203  -1.733             0.0832 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 12:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0100322  0.0003276   30.62 < 0.0000000000000002 ***
## short_listTRUE -0.0026446  0.0003762   -7.03     0.00000000000208 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0084706  0.0002257  37.532 < 0.0000000000000002 ***
## short_listTRUE 0.0015075  0.0002922   5.159          0.000000249 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0133846  0.0004574   29.26 <0.0000000000000002 ***
## short_listTRUE 0.0060865  0.0005480   11.11 <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)    0.0169555  0.0004249  39.905 < 0.0000000000000002 ***
## short_listTRUE 0.0029760  0.0005174   5.752        0.00000000883 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 16:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0135136  0.0005241  25.786 < 0.0000000000000002 ***
## short_listTRUE 0.0032587  0.0006744   4.832           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)    0.0425046  0.0003183 133.546 <0.0000000000000002 ***
## short_listTRUE 0.0008147  0.0003910   2.084              0.0372 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0268609  0.0004991   53.82 <0.0000000000000002 ***
## short_listTRUE -0.0068311  0.0006006  -11.37 <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)     0.0129066  0.0003249  39.726 < 0.0000000000000002 ***
## short_listTRUE -0.0016947  0.0003861  -4.389            0.0000114 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0086065  0.0003458   24.89 <0.0000000000000002 ***
## short_listTRUE 0.0060669  0.0004429   13.70 <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)     0.0124514  0.0003124  39.855 < 0.0000000000000002 ***
## short_listTRUE -0.0011159  0.0003980  -2.804              0.00505 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 22:
```

```
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0127297  0.0003157  40.326 <0.0000000000000002 ***
## short_listTRUE 0.0008318  0.0003993   2.083              0.0372 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 23:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0185756  0.0005551  33.463 < 0.0000000000000002 ***
## short_listTRUE -0.0027946  0.0006233  -4.484           0.00000735 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0138603  0.0002290  60.516 < 0.0000000000000002 ***
## short_listTRUE 0.0013402  0.0002851   4.702           0.00000259 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 25:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0111248  0.0001346  82.653 < 0.0000000000000002 ***
## short_listTRUE 0.0007890  0.0001684   4.686           0.00000279 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0098015  0.0002871   34.14 <0.0000000000000002 ***
## short_listTRUE 0.0037726  0.0003834    9.84 <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)    0.0103138  0.0002167  47.587 < 0.0000000000000002 ***
```

```
## short_listTRUE 0.0009108  0.0002731   3.335             0.000852 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 28:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0111592  0.0004003  27.877 < 0.0000000000000002 ***
## short_listTRUE 0.0028078  0.0005067   5.541         0.0000000302 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0105108  0.0003591  29.266 <0.0000000000000002 ***
## short_listTRUE 0.0042226  0.0004472   9.442 <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)    0.0169430  0.0004391   38.59 <0.0000000000000002 ***
## short_listTRUE 0.0007979  0.0005542    1.44                0.15
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 31:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0369173  0.0002220   166.3 <0.0000000000000002 ***
## short_listTRUE -0.0068129  0.0002827   -24.1 <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)     0.0100393  0.0001339  74.960 <0.0000000000000002 ***
## short_listTRUE -0.0002587  0.0001601  -1.616               0.106
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
##
## Topic 33:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0230283  0.0005077   45.36 <0.0000000000000002 ***
## short_listTRUE -0.0059535  0.0006388   -9.32 <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)    0.0136827  0.0004462  30.662 <0.0000000000000002 ***
## short_listTRUE 0.0010979  0.0005552   1.978               0.048 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 35:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0198285  0.0003381   58.65 <0.0000000000000002 ***
## short_listTRUE -0.0061414  0.0003909  -15.71 <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)    0.0061167  0.0003208   19.07 <0.0000000000000002 ***
## short_listTRUE 0.0041061  0.0004083   10.06 <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)    0.0069657  0.0003196  21.794 < 0.0000000000000002 ***
## short_listTRUE 0.0015000  0.0004215   3.558             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)     0.0226435  0.0005276   42.92 <0.0000000000000002 ***
## short_listTRUE -0.0073560  0.0006033  -12.19 <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)    0.0205479  0.0006330  32.459 <0.0000000000000002 ***
## short_listTRUE 0.0011686  0.0008248   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)    0.0139287  0.0003563   39.09 <0.0000000000000002 ***
## short_listTRUE 0.0047449  0.0004501   10.54 <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)     0.0107933  0.0001173   92.02 <0.0000000000000002 ***
## short_listTRUE -0.0014800  0.0001338  -11.06 <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  0.0004394  34.258 < 0.0000000000000002 ***
## short_listTRUE -0.0033632  0.0005466  -6.153       0.000000000766 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 43:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0140285  0.0004847  28.944 < 0.0000000000000002 ***
## short_listTRUE 0.0021713  0.0006060   3.583              0.00034 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 44:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0147160  0.0002666  55.195 < 0.0000000000000002 ***
## short_listTRUE 0.0016371  0.0003344   4.896          0.000000981 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 45:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0135446  0.0004531  29.893 < 0.0000000000000002 ***
## short_listTRUE -0.0036865  0.0005326  -6.922     0.00000000000448 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 46:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0067864  0.0003654   18.57 <0.0000000000000002 ***
## short_listTRUE 0.0042905  0.0004437    9.67 <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)    0.0077671  0.0003507   22.14 < 0.0000000000000002 ***
## short_listTRUE 0.0027525  0.0004454    6.18       0.000000000644 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 48:
##
## Coefficients:
##                  Estimate Std. Error t value           Pr(>|t|)
## (Intercept)     0.0225033  0.0005094   44.17 <0.0000000000000002 ***
## short_listTRUE -0.0077118  0.0005846  -13.19 <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)     0.0155770  0.0004835  32.215 < 0.0000000000000002 ***
## short_listTRUE -0.0038810  0.0005926  -6.549      0.0000000000582 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 50:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0232448  0.0006509   35.71 <0.0000000000000002 ***
## short_listTRUE -0.0076653  0.0007471  -10.26 <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)    0.0105760  0.0003567   29.65 <0.0000000000000002 ***
## short_listTRUE 0.0055916  0.0004514   12.39 <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)    0.01749013 0.00018623  93.915 <0.0000000000000002 ***
## short_listTRUE 0.00001905 0.00022924   0.083               0.934
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 53:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0107598  0.0003976  27.063 <0.0000000000000002 ***
## short_listTRUE 0.0003065  0.0004669   0.657               0.511
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 54:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0261048  0.0004279  61.000 <0.0000000000000002 ***
```

```
## short_listTRUE -0.0044993  0.0004925  -9.135 <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)     0.0101880  0.0001856  54.899 <0.0000000000000002 ***
## short_listTRUE -0.0004804  0.0002437  -1.972              0.0487 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 56:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0114035  0.0003502  32.563 < 0.0000000000000002 ***
## short_listTRUE -0.0015375  0.0004365  -3.522             0.000428 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 57:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0129069  0.0003207  40.243 < 0.0000000000000002 ***
## short_listTRUE 0.0012919  0.0004120   3.136              0.00172 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 58:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0090850  0.0002448  37.113 < 0.0000000000000002 ***
## short_listTRUE 0.0015904  0.0003330   4.775            0.0000018 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 59:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0166458  0.0001923  86.552 < 0.0000000000000002 ***
## short_listTRUE 0.0007301  0.0002314   3.155              0.00161 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
##
## Topic 60:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0100660  0.0003752  26.831 <0.0000000000000002 ***
## short_listTRUE -0.0002233  0.0004601  -0.485               0.628
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 61:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0112650  0.0001136   99.15 <0.0000000000000002 ***
## short_listTRUE 0.0019039  0.0001402   13.58 <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)     0.0104588  0.0003939  26.554 <0.0000000000000002 ***
## short_listTRUE -0.0010404  0.0004713  -2.208              0.0273 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 63:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0088039  0.0003593  24.500 < 0.0000000000000002 ***
## short_listTRUE 0.0020095  0.0004632   4.338            0.0000144 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 64:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0207843  0.0002282  91.080 < 0.0000000000000002 ***
## short_listTRUE 0.0017465  0.0003042   5.742        0.00000000942 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 65:
##
## Coefficients:
```

```
##                  Estimate Std. Error t value             Pr(>|t|)    
## (Intercept)     0.0136841  0.0003857  35.481 < 0.0000000000000002 ***
## short_listTRUE -0.0017372  0.0004613  -3.766             0.000166 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## 
## Topic 66:
## 
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)    
## (Intercept)    0.0132102  0.0004836  27.317 < 0.0000000000000002 ***
## short_listTRUE 0.0037765  0.0005855   6.451       0.000000000112 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## 
## Topic 67:
## 
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)    
## (Intercept)     0.0219813  0.0003095  71.033 < 0.0000000000000002 ***
## short_listTRUE -0.0011535  0.0003847  -2.999              0.00271 ** 
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## 
## Topic 68:
## 
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)    
## (Intercept)     0.0193964  0.0001788   108.5 <0.0000000000000002 ***
## short_listTRUE -0.0026870  0.0002297   -11.7 <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)     0.00275135  0.00001988 138.408 <0.0000000000000002 ***
## short_listTRUE -0.00002552  0.00002595  -0.983               0.325    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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