All Women Short lists Methodology

Contents

TO DO:

1. Run the same STM stuff as below, but with the K30 one

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 experimented with unsupervised Latent Dirichlet Allocation (Blei, Ng, & Jordan, 2003), and trained a Naive Bayes classifier to distinguish AWS and non-AWS speeches.

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

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.

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

Following 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 2: Number of Speeches and Words in Dataset

Gender	Speeches	Words
All	656412	111180398
Female	148702	26231034
Male	507710	84949364
Conservatives		
All	285291	44800169
Female	48768	7363031
Male	236523	37437138
Labour		
All	261942	46494850
Female	84569	15897929
Non-All Women Shortlists	28695	5422776
All Women Shortlists	55874	10475153
Male	177373	30596921
Liberal Democrat		
All	72716	13485902
Female	7552	1503459
Male	65164	11982443
Other		
All	36463	6399477
Female	7813	1466615
Male	28650	4932862

Descriptive Statistics

Data in this table 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.

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).

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.

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## transparency is not supported on this device: reported only once per page
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There are no categories among female Labour MPs by selection process meeting the |0.2| threshold. Only one category – first person plural pronouns, d=0.19 – exceeded |0.1|.

[1] 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 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

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

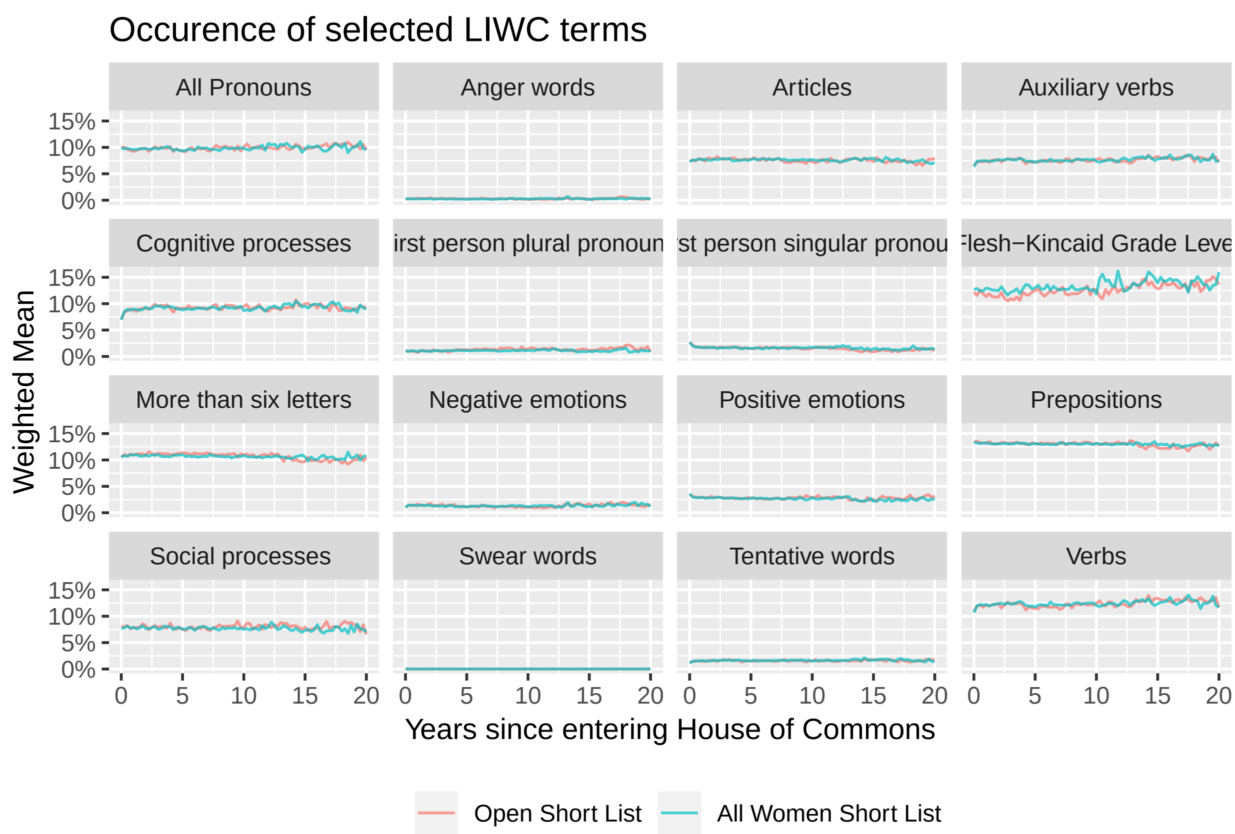


Figure 1: Occurence of selected LIWC terms

Conservatives vs Labour

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

All MPs Gender Differences

POS Analysis

Part-of-speech (POS) tagging was done using `spaCy` (Honnibal & Montani, 2017) and the `spacyr` package (Benoit & Matsuo, 2018).

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.

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.

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	-0.04	negligible
Plural Nouns	5.85	3.72	5.03	3.79	-0.16	negligible
Singular Nouns	15.62	9.84	16.01	11.19	0.02	negligible
Adjectives	9.58	4.78	9.28	5.29	-0.02	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

Unsurprisingly, despite male MPs saying almost twice as many words (30601887 vs 15898845) 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 refer to “women's” and “woman”. 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 MPs are more comfortable using the traditional language of House of Commons debate.

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.

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.

[2]Special Educational Needs

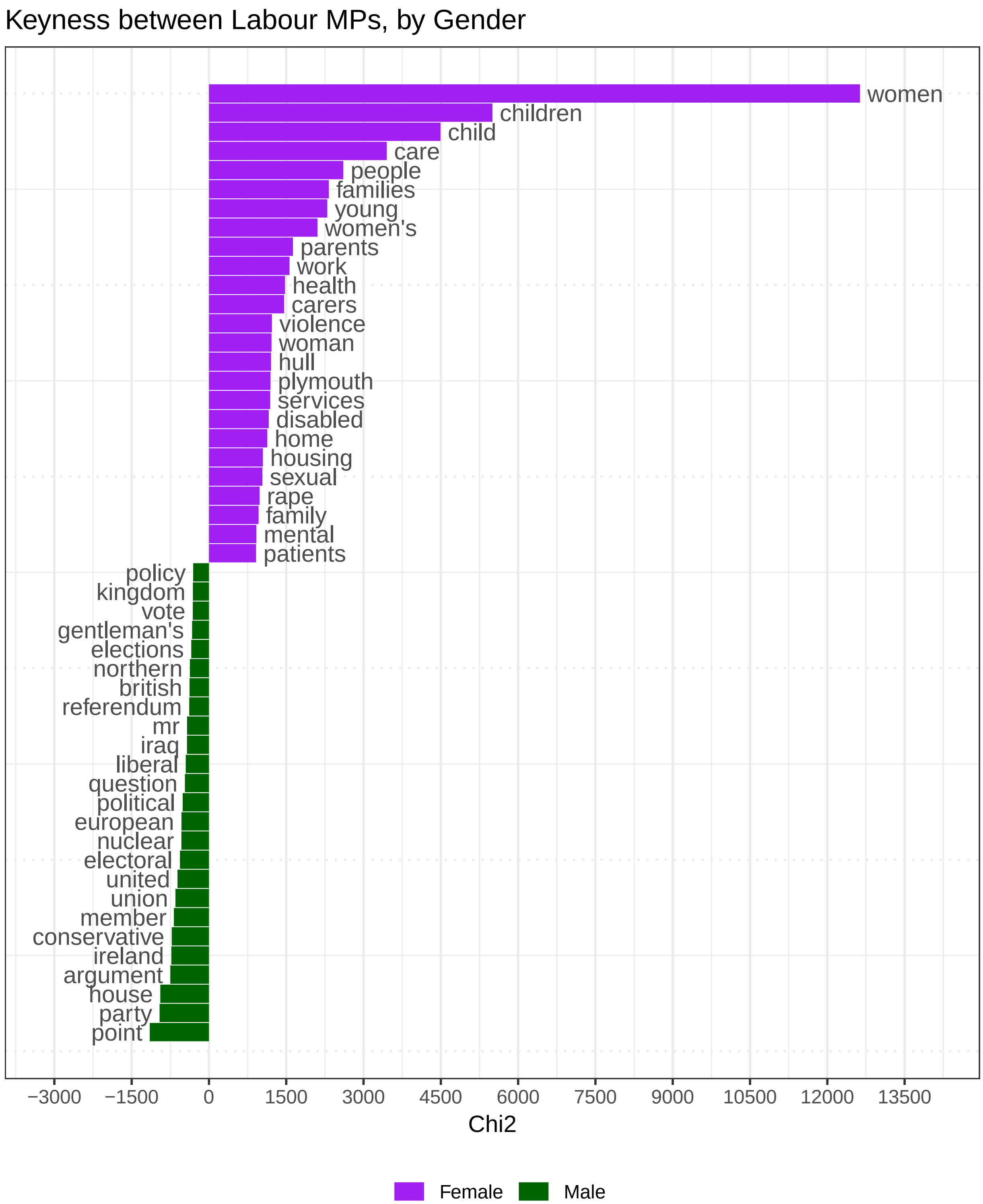


Figure 2: Keyness between Labour MPs, by Gender

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.

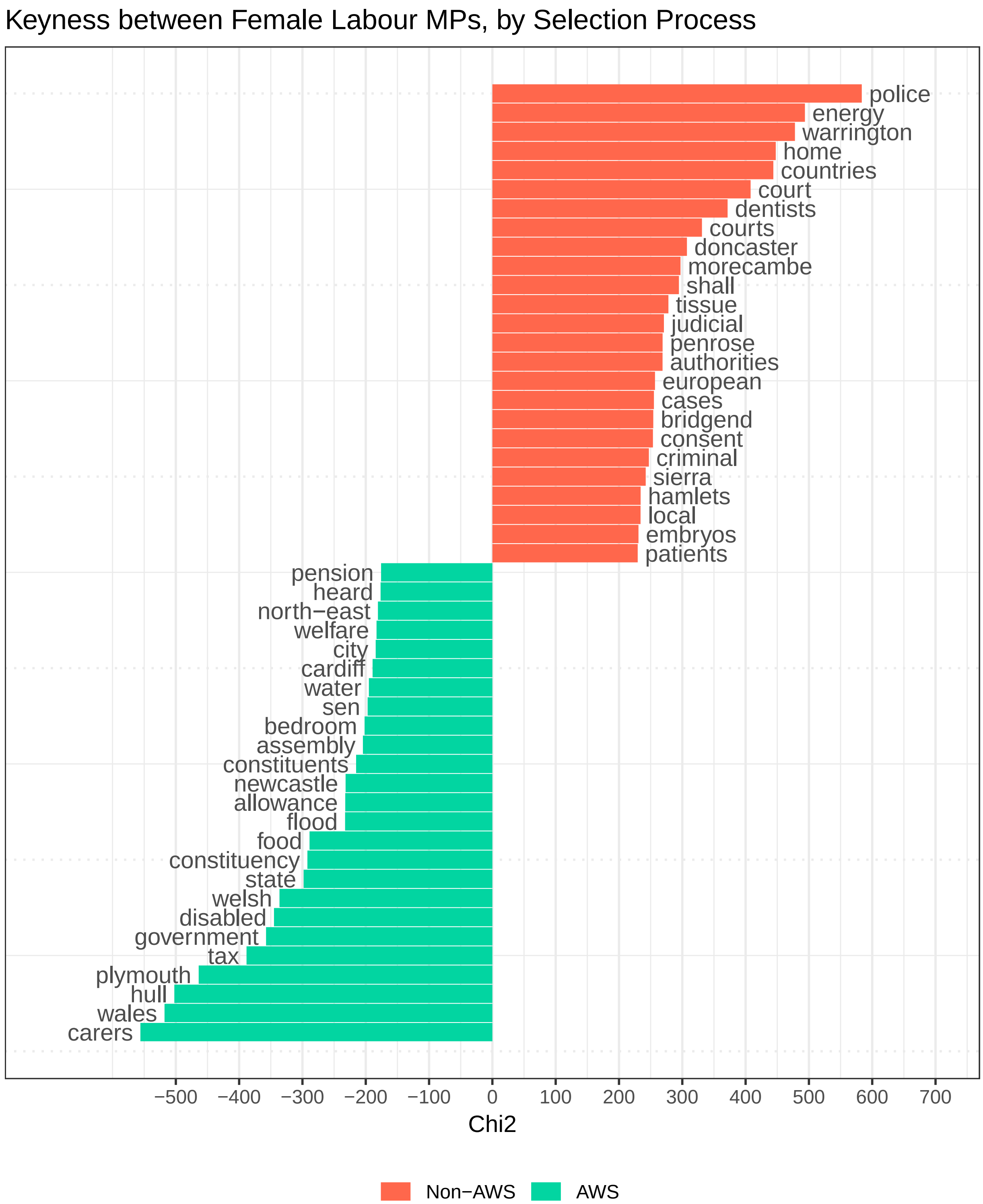


Figure 3: Keyness between Female Labour MPs, by Selection Process

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

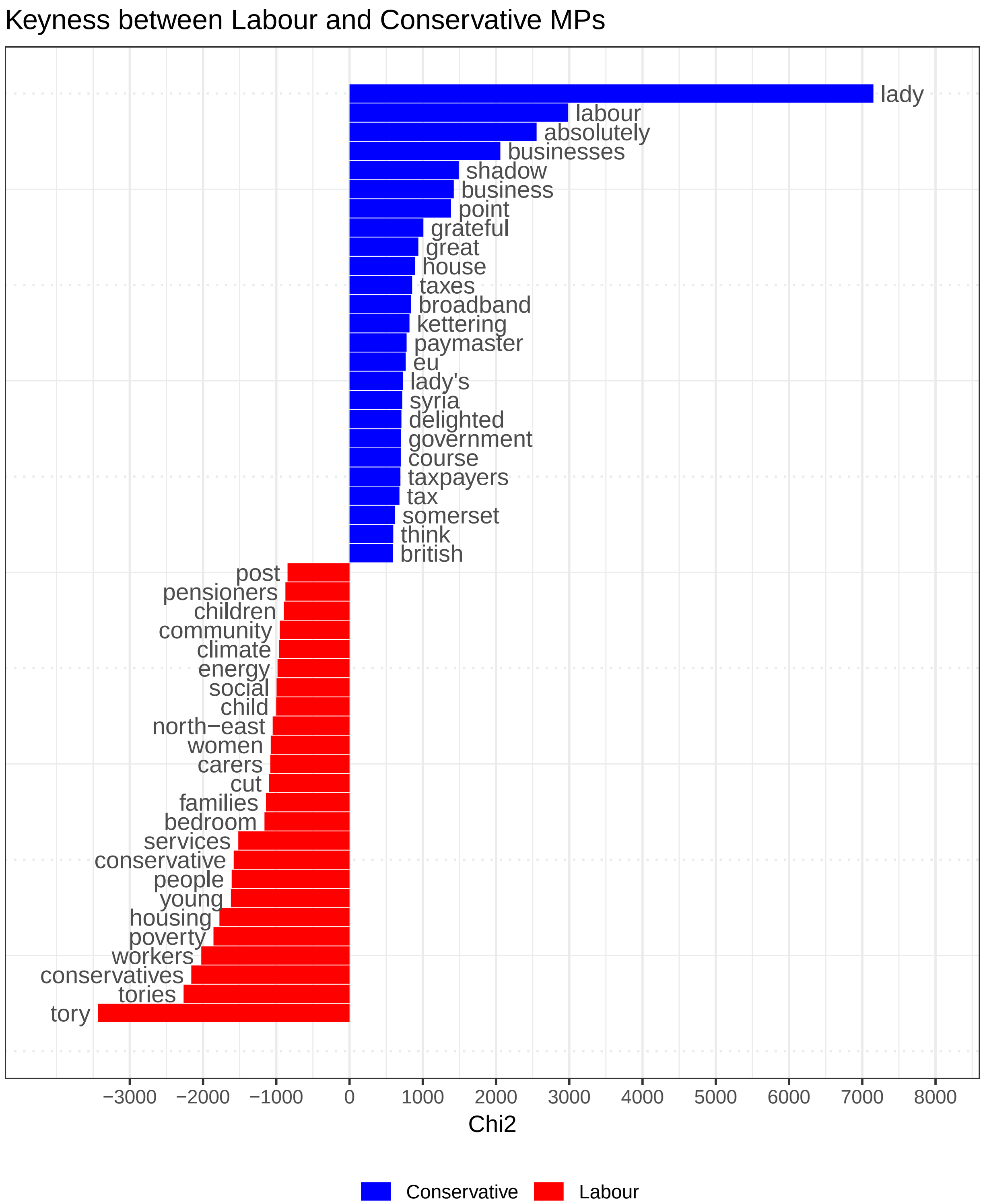


Figure 4: Keyness between Labour and Conservative MPs

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.

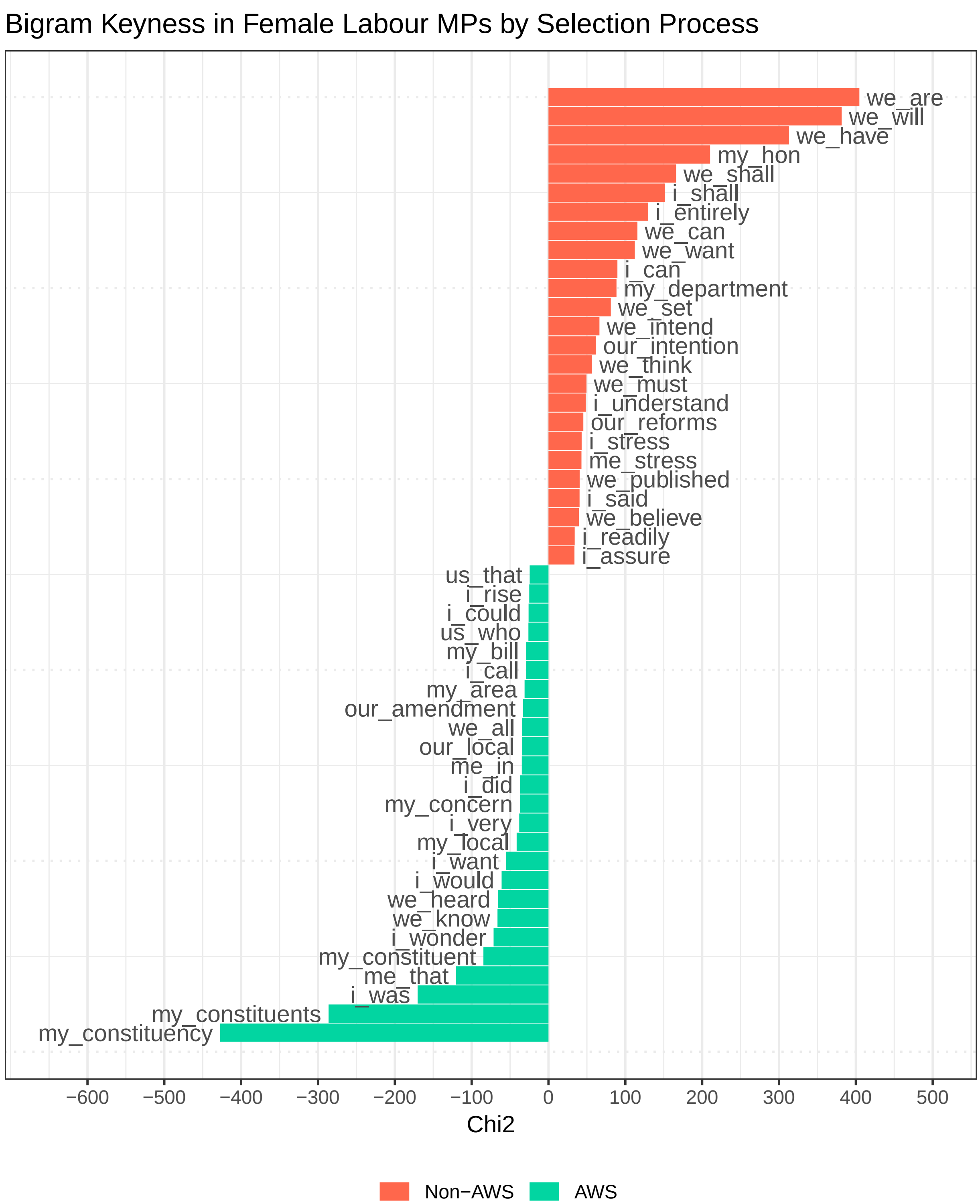


Figure 5: Bigram Keyness in Female Labour MPs by Selection Process

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. We incorporated the AWS status of speakers into our topic model.

Short lists vs Non-Short lists - K69

We used an algorithm developed by Lee and 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, with a number of topics lacking clear boundaries between them.

We created a Fruchterman-Reingold (Fruchterman & Reingold, 1991) diagram of all 69 topic models. Larger vertices indicate more common topics, and the plot implements 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. 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.

Table 9: 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%	4,759	2.81%

Table 9: Count and Distribution of Topics – K69 *(continued)*

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
Topic 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%	6,078	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%

Table 9: Count and Distribution of Topics – K69 *(continued)*

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
Topic 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%

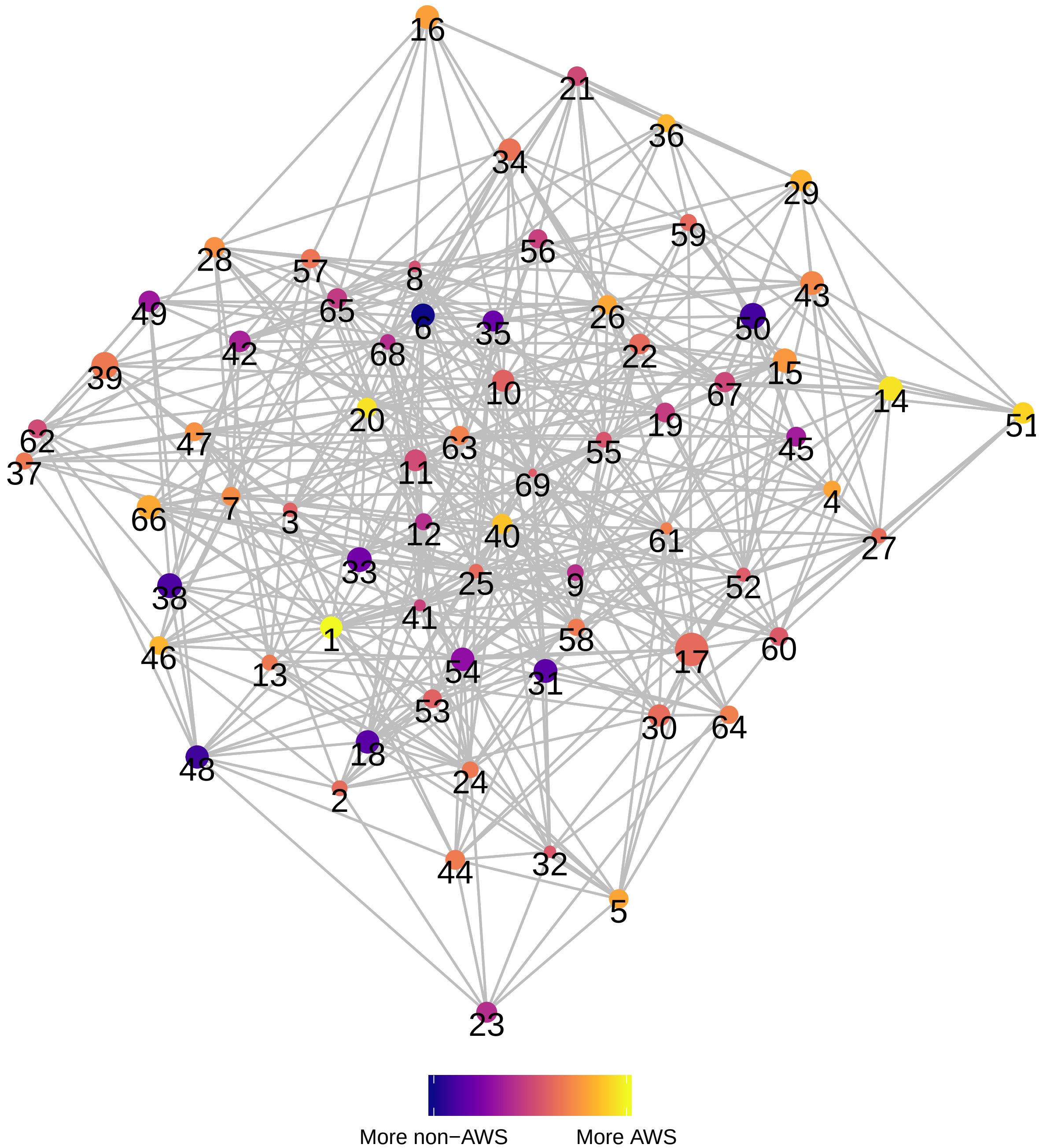
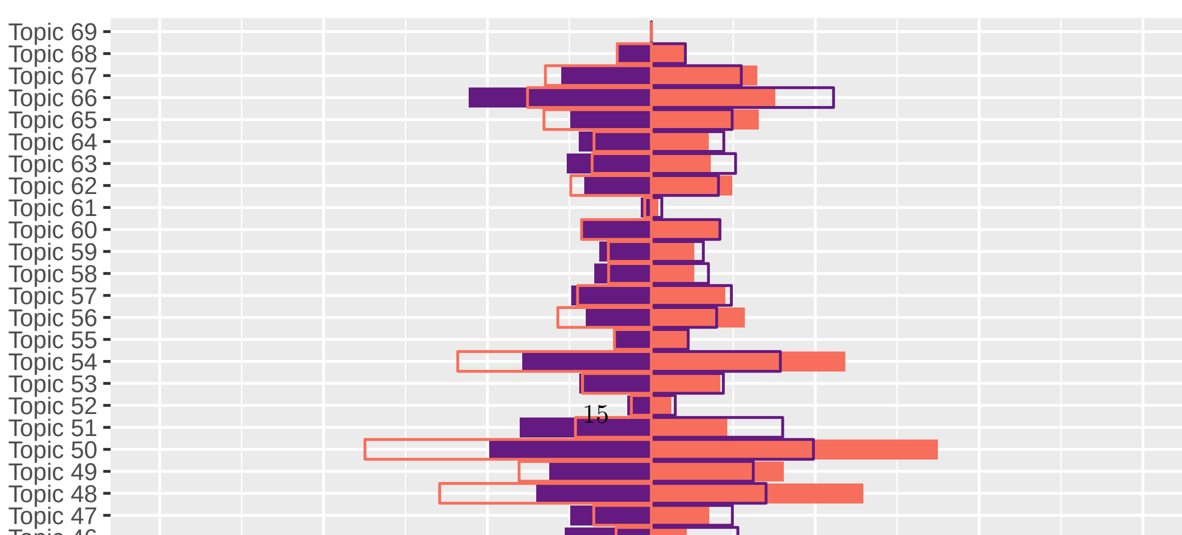


Figure 6: Fruchterman-Reingold plot of K69 Network



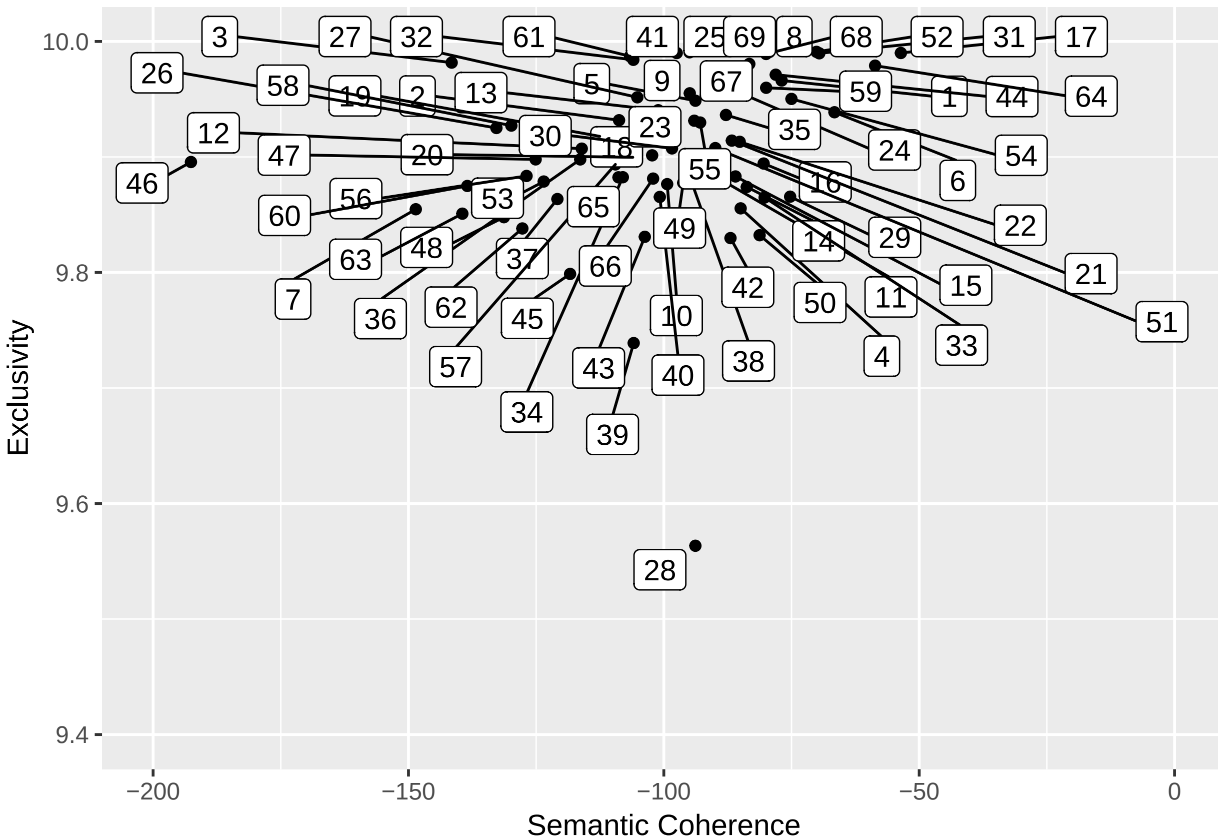
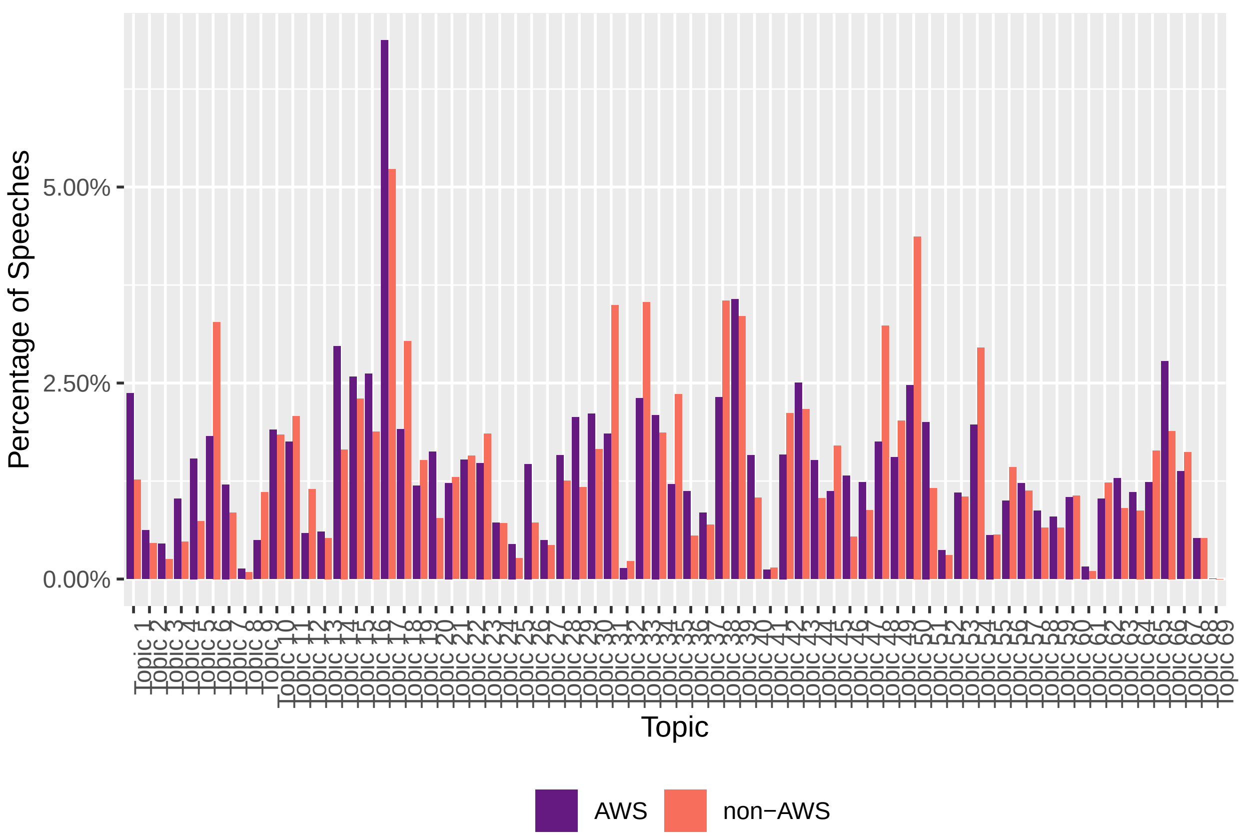


Figure 7: Coherence of K69 Topic Models



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).

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

(continued)

Topic Number	Top Ten Words	Top Ten FREX
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

(continued)

Topic Number	Top Ten Words	Top Ten FREX
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

(continued)

Topic Number	Top Ten Words	Top Ten FREX
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

(continued)

Topic Number	Top Ten Words	Top Ten FREX
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

Short lists vs Non-Short lists - K30

However, as seen in the word lists above, there is relatively scattershot semantic coherence, although exclusivity is high, when using 69 topic models. We therefore re-ran the analysis, using 30 topic models, which has resulted in increased semantic coherence, albeit with slightly lower exclusivity.

Table 11: Count and Distribution of Topics – K30

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
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	1,303	2.43%	900	3.23%	3,364	1.99%
Topic 5	1,976	3.68%	1,371	4.91%	9,653	5.7%
Topic 6	1,720	3.2%	623	2.23%	4,562	2.69%
Topic 7	2,721	5.07%	758	2.72%	4,045	2.39%
Topic 8	879	1.64%	381	1.37%	2,192	1.29%
Topic 9	1,008	1.88%	743	2.66%	1,747	1.03%
Topic 10	1,351	2.52%	658	2.36%	6,235	3.68%
Topic 11	2,144	3.99%	1,552	5.56%	4,494	2.65%
Topic 12	2,507	4.67%	883	3.16%	10,394	6.14%
Topic 13	1,231	2.29%	825	2.96%	3,972	2.35%
Topic 14	984	1.83%	646	2.32%	1,570	0.93%
Topic 15	1,180	2.2%	1,410	5.05%	4,935	2.91%
Topic 16	2,175	4.05%	1,302	4.67%	7,547	4.46%
Topic 17	5,309	9.89%	2,357	8.45%	25,255	14.91%
Topic 18	2,362	4.4%	1,003	3.59%	6,230	3.68%
Topic 19	1,183	2.2%	445	1.59%	3,305	1.95%
Topic 20	1,334	2.48%	561	2.01%	2,075	1.23%
Topic 21	4,361	8.12%	1,556	5.58%	11,845	6.99%
Topic 22	977	1.82%	359	1.29%	2,259	1.33%
Topic 23	1,787	3.33%	890	3.19%	6,124	3.62%
Topic 24	813	1.51%	233	0.84%	2,132	1.26%
Topic 25	1,604	2.99%	1,104	3.96%	4,917	2.9%
Topic 26	1,237	2.3%	664	2.38%	1,105	0.65%
Topic 27	668	1.24%	325	1.16%	1,796	1.06%
Topic 28	3,218	5.99%	1,001	3.59%	8,906	5.26%

Table 11: Count and Distribution of Topics – K30 *(continued)*

Topic Number	AWS Speeches	Percent of AWS Speeches	Non-AWS Speeches	Percent of non-AWS Speeches	Male MP Speeches	Percent of Male MP Speeches
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%

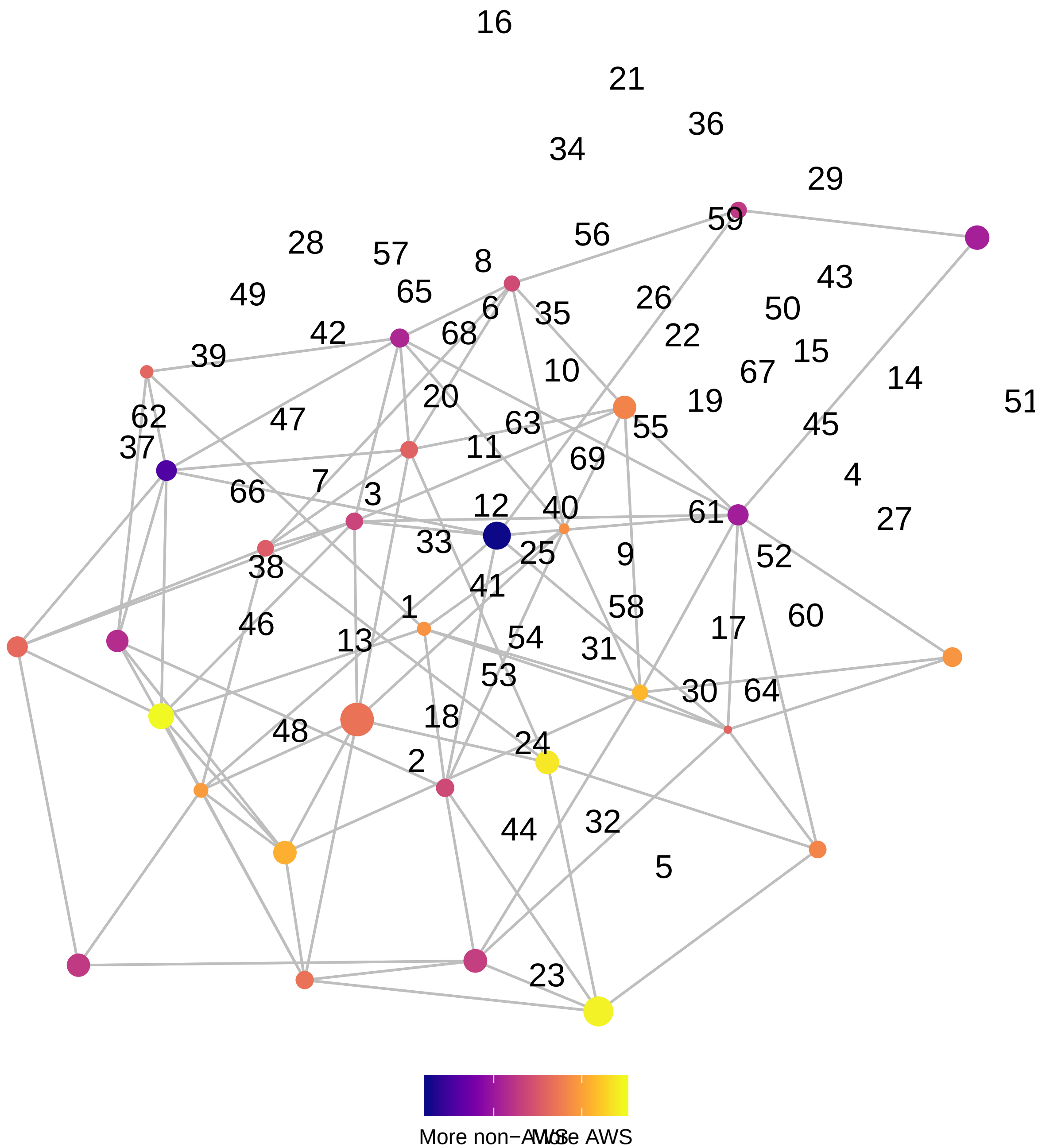
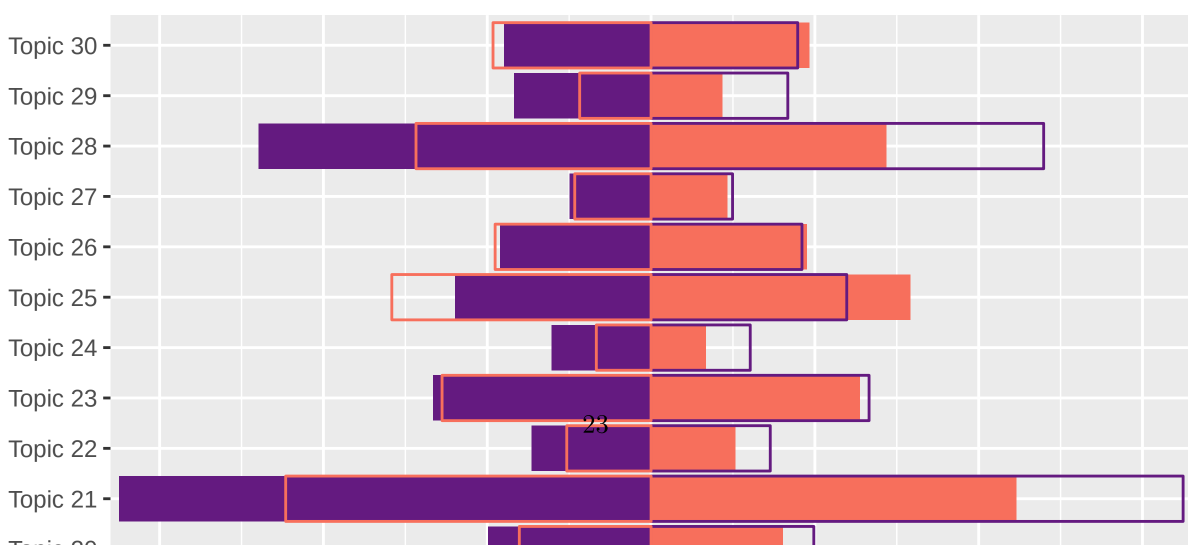


Figure 8: Fruchterman-Reingold plot of K30 Network



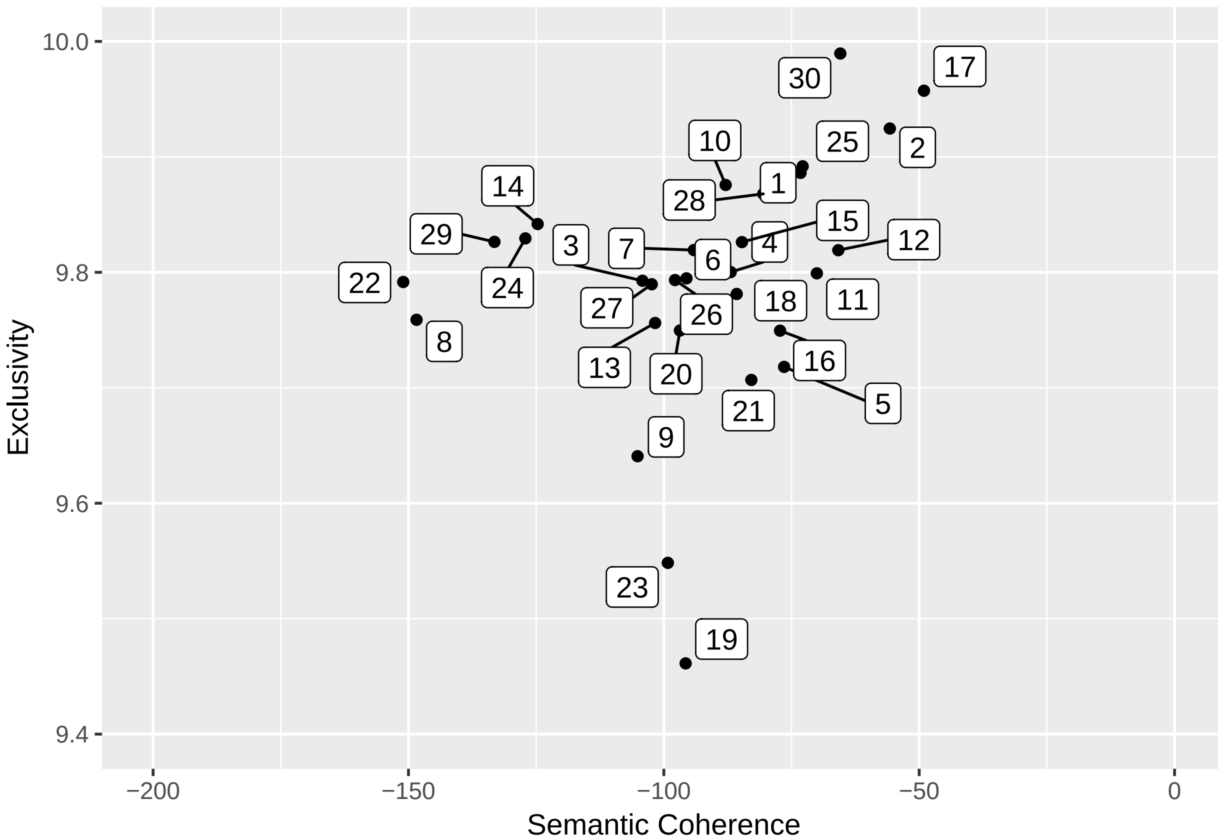
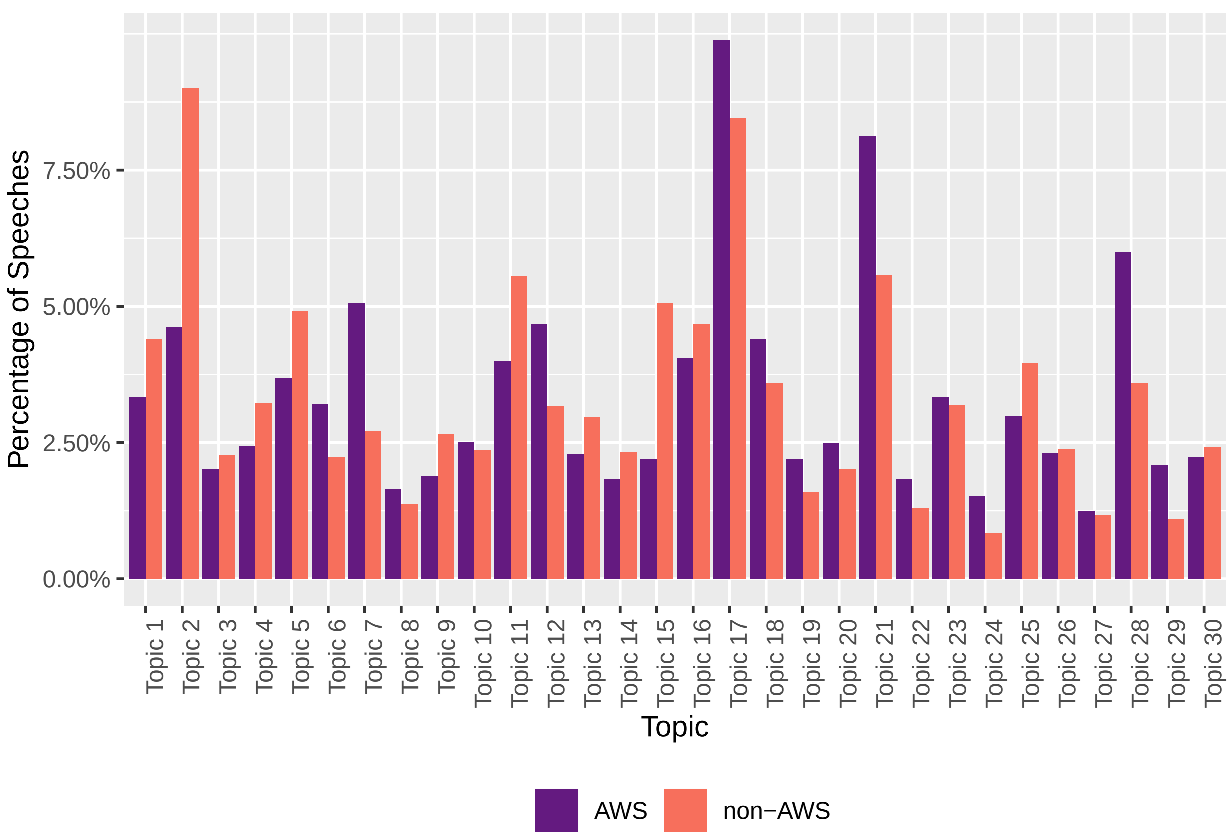


Figure 9: Coherence of K30 Topic Models



Word Occurences

Table 12: Words in topic

Topic Number	Top Ten Words	Top Ten FREX
Topic 1	bill, amendment, clause, new, legislation, amendments, act, committee, provisions, 1	amendment, clause, amendments, clauses, nos, insert, subsection, provisions, bill, tabled
Topic 2	issues, public, information, also, report, review, process, work, need, important	consultation, review, guidance, recommendations, information, considering, decisions, arrangements, framework, detailed
Topic 3	women, men, pay, equality, rights, women's, discrimination, equal, work, woman	women, equality, gender, equalities, bishops, discrimination, female, women's, equal, men
Topic 4	police, crime, officers, behaviour, policing, home, antisocial, community, work, force	policing, antisocial, constable, burglary, wardens, crime, constabulary, police, officers, pcsos
Topic 5	european, uk, countries, eu, union, trade, international, united, world, british	treaty, enlargement, wto, lisbon, doha, eu, eu's, mod, multilateral, accession
Topic 6	transport, london, rail, bus, road, services, line, travel, network, train	rail, bus, passengers, fares, trains, buses, passenger, heathrow, congestion, hs2
Topic 7	people, work, benefit, pension, benefits, support, disabled, employment, carers, working	disabled, jobcentre, incapacity, carers, pension, claimants, esa, dla, pensions, atos
Topic 8	immigration, safety, uk, asylum, enforcement, home, number, illegal, licensing, animals	dogs, dog, id, visa, fur, mink, hse, sia, seekers, fireworks
Topic 9	health, research, cancer, treatment, medical, disease, can, smoking, patients, people	cancer, diseases, vaccine, flu, embryos, infections, diabetes, palliative, prostate, cervical
Topic 10	government, labour, conservative, party, opposition, policy, government's, scotland, scottish, members	conservative, liberal, democrats, conservatives, scottish, democrat, scotland, tory, interruption, tories
Topic 11	care, health, nhs, services, service, hospital, patients, staff, trust, social	dentists, ambulance, dentistry, helier, dentist, nurses, hospital, pct, hospitals, dental
Topic 12	member, members, debate, house, mr, committee, said, time, speaker, north	member, speaker, mr, debate, spoke, thoughtful, backbench, debates, madam, select
Topic 13	companies, financial, company, market, scheme, money, debt, consumers, bank, credit	payday, annuity, oft, policyholders, penrose, fca, loan, prepayment, loans, annuities
Topic 14	young, people, health, mental, youth, prison, problems, drugs, alcohol, drug	prisons, probation, cannabis, reoffending, mental, prison, self-harm, youth, alcohol, sentences
Topic 15	cases, court, legal, law, case, justice, evidence, criminal, courts, home	judicial, attorney-general, defendant, extradition, tpims, suspects, court, courts, prosecution, isc
Topic 16	energy, businesses, business, jobs, investment, economy, industry, economic, new, sector	carbon, renewable, renewables, solar, low-carbon, energy, feed-in, manufacturing, steel, businesses

Table 12: Words in topic *(continued)*

Topic Number	Top Ten Words	Top Ten FREX
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

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?

Appendix

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-signatur
##       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
```

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)    0.0169820  0.0003020   56.23 <0.0000000000000002 ***
## short_listTRUE 0.0069368  0.0003971   17.47 <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)    0.0058321  0.0002422  24.081 <0.0000000000000002 ***
## short_listTRUE 0.0007653  0.0003101   2.468              0.0136 *
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 3:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0087310  0.0001132  77.123 <0.0000000000000002 ***
## short_listTRUE 0.0001952  0.0001366   1.429               0.153
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 4:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0065016  0.0003143  20.687 <0.0000000000000002 ***
## short_listTRUE 0.0035549  0.0004269   8.327 <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)    0.0120174  0.0002520   47.69 <0.0000000000000002 ***
## short_listTRUE 0.0036189  0.0003373   10.73 <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)     0.0314341  0.0004293   73.22 <0.0000000000000002 ***
## short_listTRUE -0.0094474  0.0004854  -19.46 <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)    0.0081445  0.0003874  21.025 < 0.0000000000000002 ***
## short_listTRUE 0.0024572  0.0004907   5.007          0.000000553 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 8:
```

```
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0156074  0.0001149 135.825 < 0.0000000000000002 ***
## short_listTRUE -0.0006839  0.0001365  -5.012          0.000000541 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 9:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0107663  0.0002821  38.160 < 0.0000000000000002 ***
## short_listTRUE -0.0025556  0.0003431  -7.449   0.0000000000000953 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0147993  0.0004900    30.2 <0.0000000000000002 ***
## short_listTRUE 0.0002528  0.0006320     0.4               0.689
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0131126  0.0004146  31.624 <0.0000000000000002 ***
## short_listTRUE -0.0008800  0.0005291  -1.663              0.0963 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 12:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0100852  0.0003095  32.589 < 0.0000000000000002 ***
## short_listTRUE -0.0026481  0.0003691  -7.176    0.000000000000726 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 13:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0084450  0.0002191  38.551 < 0.0000000000000002 ***
```

```
## short_listTRUE 0.0014899  0.0002687   5.545         0.0000000294 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0133438  0.0004470   29.85 <0.0000000000000002 ***
## short_listTRUE 0.0061503  0.0005902   10.42 <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)    0.0169350  0.0004534  37.351 < 0.0000000000000002 ***
## short_listTRUE 0.0029624  0.0005805   5.103          0.000000334 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 16:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0134130  0.0004827  27.788 < 0.0000000000000002 ***
## short_listTRUE 0.0033611  0.0006348   5.294           0.00000012 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 17:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0425789  0.0003234  131.67 <0.0000000000000002 ***
## short_listTRUE 0.0007580  0.0004032    1.88              0.0601 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0269673  0.0004306   62.63 <0.0000000000000002 ***
## short_listTRUE -0.0068823  0.0005341  -12.88 <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)     0.0129234  0.0003316  38.969 < 0.0000000000000002 ***
## short_listTRUE -0.0017505  0.0004011  -4.364            0.0000128 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 20:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0085543  0.0003335   25.65 <0.0000000000000002 ***
## short_listTRUE 0.0061103  0.0004033   15.15 <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)     0.0124201  0.0003116  39.861 < 0.0000000000000002 ***
## short_listTRUE -0.0010573  0.0004025  -2.627              0.00861 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 22:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0127975  0.0003358  38.115 <0.0000000000000002 ***
## short_listTRUE 0.0008161  0.0004069   2.006              0.0449 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 23:
##
## Coefficients:
##                   Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0183918  0.0004765  38.601 < 0.0000000000000002 ***
## short_listTRUE -0.0026629  0.0005902  -4.512           0.00000643 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
```

```
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0137655  0.0002352  58.530 < 0.0000000000000002 ***
## short_listTRUE 0.0014429  0.0003001   4.808           0.00000152 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 25:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0111115  0.0001292  86.025 < 0.0000000000000002 ***
## short_listTRUE 0.0007926  0.0001661   4.771           0.00000184 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 26:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0098091  0.0002868   34.20 <0.0000000000000002 ***
## short_listTRUE 0.0036611  0.0003538   10.35 <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)    0.0103176  0.0002343  44.036 < 0.0000000000000002 ***
## short_listTRUE 0.0008861  0.0002611   3.394             0.000689 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 28:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.011297   0.000428  26.394 < 0.0000000000000002 ***
## short_listTRUE 0.002664   0.000515   5.173           0.00000023 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 29:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0105473  0.0003633  29.029 <0.0000000000000002 ***
## short_listTRUE 0.0041838  0.0004561   9.172 <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)    0.0168601  0.0004028   41.86 <0.0000000000000002 ***
## short_listTRUE 0.0008545  0.0005242    1.63               0.103
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 31:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0369130  0.0002499   147.7 <0.0000000000000002 ***
## short_listTRUE -0.0067770  0.0002986   -22.7 <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)     0.0100341  0.0001399  71.744 <0.0000000000000002 ***
## short_listTRUE -0.0002302  0.0001752  -1.314               0.189
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 33:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0230465  0.0005251  43.886 <0.0000000000000002 ***
## short_listTRUE -0.0058599  0.0005937  -9.871 <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)    0.0135926  0.0004178  32.536 <0.0000000000000002 ***
## short_listTRUE 0.0011910  0.0005199   2.291               0.022 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 35:
```

```
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0198427  0.0003762   52.74 <0.0000000000000002 ***
## short_listTRUE -0.0061630  0.0004266  -14.45 <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)    0.0060886  0.0003228   18.86 <0.0000000000000002 ***
## short_listTRUE 0.0042336  0.0003931   10.77 <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)    0.0069614  0.0003201  21.746 < 0.0000000000000002 ***
## short_listTRUE 0.0015241  0.0004066   3.748             0.000178 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 38:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0226163  0.0005456   41.45 <0.0000000000000002 ***
## short_listTRUE -0.0073797  0.0006696  -11.02 <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)    0.0203911  0.0006369  32.017 <0.0000000000000002 ***
## short_listTRUE 0.0014651  0.0008155   1.796              0.0724 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 40:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0138937  0.0003323   41.81 <0.0000000000000002 ***
```

```
## short_listTRUE 0.0047976  0.0004591   10.45 <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)     0.0108007  0.0001098   98.39 <0.0000000000000002 ***
## short_listTRUE -0.0014971  0.0001310  -11.43 <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)     0.0150661  0.0004851  31.059 < 0.0000000000000002 ***
## short_listTRUE -0.0033915  0.0005927  -5.722         0.0000000106 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 43:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0139623  0.0005250  26.592 < 0.0000000000000002 ***
## short_listTRUE 0.0022108  0.0006178   3.578             0.000346 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 44:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0146771  0.0002625   55.91 < 0.0000000000000002 ***
## short_listTRUE 0.0016747  0.0003246    5.16          0.000000248 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 45:
##
## Coefficients:
##                   Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0135184  0.0004119  32.816 < 0.0000000000000002 ***
## short_listTRUE -0.0036628  0.0004959  -7.386    0.000000000000153 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
##
## Topic 46:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0068278  0.0003477  19.634 <0.0000000000000002 ***
## short_listTRUE 0.0042234  0.0004546   9.291 <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)    0.0077418  0.0003305  23.426 < 0.0000000000000002 ***
## short_listTRUE 0.0026976  0.0004374   6.167       0.000000000698 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 48:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0226454  0.0005433   41.69 <0.0000000000000002 ***
## short_listTRUE -0.0079187  0.0006685  -11.85 <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)     0.0156319  0.0004938  31.655 < 0.0000000000000002 ***
## short_listTRUE -0.0039197  0.0006042  -6.488      0.0000000000875 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 50:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0232769  0.0005831   39.92 <0.0000000000000002 ***
## short_listTRUE -0.0077308  0.0007148  -10.81 <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)    0.0106251  0.0003942   26.95 <0.0000000000000002 ***
## short_listTRUE 0.0054680  0.0004879   11.21 <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)    0.0174768  0.0001829  95.554 <0.0000000000000002 ***
## short_listTRUE 0.0000249  0.0002186   0.114               0.909
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 53:
##
## Coefficients:
##                Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0107594  0.0004470  24.071 <0.0000000000000002 ***
## short_listTRUE 0.0003102  0.0005093   0.609               0.542
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 54:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0260721  0.0003901  66.838 <0.0000000000000002 ***
## short_listTRUE -0.0045250  0.0004738  -9.551 <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)     0.0101731  0.0002063  49.301 <0.0000000000000002 ***
## short_listTRUE -0.0004771  0.0002563  -1.861              0.0627 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 56:
##
## Coefficients:
##                 Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     0.0114909  0.0003619  31.753 < 0.0000000000000002 ***
## short_listTRUE -0.0016179  0.0003948  -4.098            0.0000416 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 57:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0129535  0.0003331  38.892 < 0.0000000000000002 ***
## short_listTRUE 0.0013001  0.0003818   3.405            0.000662 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 58:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0090760  0.0002695  33.680 < 0.0000000000000002 ***
## short_listTRUE 0.0016117  0.0003644   4.423          0.00000974 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 59:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0166856  0.0001997  83.568 < 0.0000000000000002 ***
## short_listTRUE 0.0007154  0.0002435   2.937             0.00331 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 60:
##
## Coefficients:
##                  Estimate Std. Error t value           Pr(>|t|)
## (Intercept)     0.0100237  0.0004077  24.588 <0.0000000000000002 ***
## short_listTRUE -0.0001843  0.0004881  -0.378              0.706
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 61:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0112960  0.0001244   90.78 <0.0000000000000002 ***
## short_listTRUE 0.0018847  0.0001553   12.14 <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)     0.0104266  0.0004094  25.469 <0.0000000000000002 ***
## short_listTRUE -0.0009740  0.0004851  -2.008              0.0447 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 63:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0088646  0.0003750   23.64 < 0.0000000000000002 ***
## short_listTRUE 0.0018958  0.0004646    4.08             0.000045 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 64:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0207664  0.0002094  99.192 < 0.0000000000000002 ***
## short_listTRUE 0.0017969  0.0002734   6.571      0.0000000000503 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 65:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0138312  0.0004248   32.56 < 0.0000000000000002 ***
## short_listTRUE -0.0018987  0.0005456   -3.48             0.000502 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 66:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0132907  0.0005206  25.530 < 0.0000000000000002 ***
## short_listTRUE 0.0037640  0.0006552   5.745        0.00000000922 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 67:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0220143  0.0003138  70.157 < 0.0000000000000002 ***
```

```
## short_listTRUE -0.0012024  0.0003784  -3.178             0.00149 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 68:
##
## Coefficients:
##                  Estimate Std. Error t value           Pr(>|t|)
## (Intercept)     0.0194280  0.0001503   129.3 <0.0000000000000002 ***
## short_listTRUE -0.0027217  0.0001779   -15.3 <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)     0.00275355  0.00001992 138.246 <0.0000000000000002 ***
## short_listTRUE -0.00002510  0.00002418  -1.038               0.299
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 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
```

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)     0.0448651  0.0007169  62.579 < 0.0000000000000002 ***
## short_listTRUE -0.0067315  0.0008824  -7.629   0.0000000000000239 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 2:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0756422  0.0005854  129.22 <0.0000000000000002 ***
## short_listTRUE -0.0214663  0.0007235  -29.67 <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)     0.0230137  0.0005809  39.620 <0.0000000000000002 ***
## short_listTRUE -0.0006309  0.0007129  -0.885               0.376
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
##
## Topic 4:
##
## Coefficients:
##                   Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0289715  0.0006726  43.072 <0.0000000000000002 ***
## short_listTRUE -0.0074848  0.0008282  -9.037 <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)     0.0367943  0.0006899  53.336 < 0.0000000000000002 ***
## short_listTRUE -0.0050875  0.0008217  -6.192       0.000000000599 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 6:
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)    0.0217272  0.0006048  35.926 < 0.0000000000000002 ***
## short_listTRUE 0.0056266  0.0007416   7.587    0.000000000000033 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 7:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0298373  0.0006397   46.64 <0.0000000000000002 ***
## short_listTRUE 0.0131763  0.0008476   15.55 <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)    0.0185099  0.0005204  35.569 <0.0000000000000002 ***
## short_listTRUE 0.0005187  0.0006270   0.827               0.408
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 9:
##
```

```
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0250590  0.0006346  39.488 < 0.0000000000000002 ***
## short_listTRUE -0.0052065  0.0007640  -6.815     0.00000000000952 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 10:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0379444  0.0004528  83.797 < 0.0000000000000002 ***
## short_listTRUE 0.0019500  0.0005662   3.444             0.000573 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 11:
##
## Coefficients:
##                  Estimate Std. Error t value           Pr(>|t|)
## (Intercept)     0.0408927  0.0008523  47.980 <0.0000000000000002 ***
## short_listTRUE -0.0083876  0.0010163  -8.253 <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)    0.0390706  0.0006211   62.90 <0.0000000000000002 ***
## short_listTRUE 0.0082080  0.0007217   11.37 <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)     0.0303216  0.0006397  47.401 < 0.0000000000000002 ***
## short_listTRUE -0.0030990  0.0007851  -3.947            0.0000792 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 14:
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     0.0238024  0.0005194  45.826 < 0.0000000000000002 ***
## short_listTRUE -0.0030014  0.0006583  -4.559           0.00000514 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 15:
##
## Coefficients:
##                  Estimate Std. Error t value           Pr(>|t|)
## (Intercept)     0.0408942  0.0006578   62.17 <0.0000000000000002 ***
## short_listTRUE -0.0166559  0.0007726  -21.56 <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)     0.0382261  0.0006828  55.987 < 0.0000000000000002 ***
## short_listTRUE -0.0044233  0.0008357  -5.293         0.000000121 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 17:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0788945  0.0006293 125.359 <0.0000000000000002 ***
## short_listTRUE 0.0018487  0.0008125   2.275             0.0229 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 18:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0298667  0.0006865  43.504 < 0.0000000000000002 ***
## short_listTRUE 0.0038156  0.0008143   4.686          0.00000279 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 19:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0196325  0.0005578   35.19 <0.0000000000000002 ***
## short_listTRUE 0.0090039  0.0006957   12.94 <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)    0.0204844  0.0005814  35.230 < 0.0000000000000002 ***
## short_listTRUE 0.0039783  0.0006919   5.749        0.00000000898 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 21:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0461970  0.0007875   58.66 <0.0000000000000002 ***
## short_listTRUE 0.0140318  0.0009902   14.17 <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)    0.0140305  0.0004536  30.933 <0.0000000000000002 ***
## short_listTRUE 0.0054540  0.0005824   9.364 <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)    0.0261956  0.0007052  37.146 <0.0000000000000002 ***
## short_listTRUE 0.0008807  0.0008619   1.022               0.307
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 24:
##
## Coefficients:
##                 Estimate Std. Error t value           Pr(>|t|)
## (Intercept)    0.0123298  0.0004207   29.31 <0.0000000000000002 ***
## short_listTRUE 0.0050251  0.0005790    8.68 <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)     0.0427882  0.0006121   69.90 <0.0000000000000002 ***
## short_listTRUE -0.0087461  0.0006893  -12.69 <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)     0.025000647  0.000512497  48.782 <0.0000000000000002 ***
## short_listTRUE -0.000006696  0.000617326  -0.011               0.991
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 27:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0149745  0.0004305  34.786 <0.0000000000000002 ***
## short_listTRUE 0.0002516  0.0005104   0.493               0.622
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Topic 28:
##
## Coefficients:
##                 Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    0.0425978  0.0005722   74.45 <0.0000000000000002 ***
## short_listTRUE 0.0146072  0.0007497   19.48 <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)    0.0188054  0.0004962  37.900 <0.0000000000000002 ***
## short_listTRUE 0.0062661  0.0006544   9.576 <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)     0.0526243  0.0003478 151.324 <0.0000000000000002 ***
## short_listTRUE -0.0036914  0.0004254  -8.678 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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