The Effect of Events on Discussion in the Australian Federal Parliament (1901–2017) *

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We systematically analyse how parliamentary discussion changes in response to different types of events in Australian history. We first create a dataset of what was said in the Australian Federal Parliament from 1901 through to 2017 based on available public records. To reduce the dimensionality of this dataset we use a correlated topic model. We analyse the effect of various events using a Bayesian hierarchical Dirichlet model. We find that: 1) changes in government tend be associated with topic changes even when the party in power does not change; 2) elections that do not result in a change in government are rarely associated with topic changes; 3) economic events, such as financial crises, have less significant and persistent effects than other events such as terrorist attacks. Our findings have implications for how we think about the longer-term trajectory of government policymaking as the media and political cycle becomes increasingly focused on short-term events.

Keywords: text analysis, politics, Australia

1   Introduction

Government policy is partly driven by parliamentary discussion. Conversely, that same discussion can indicate a government's priorities. But major events–both expected, such as an election, and unexpected, such as a recession or terrorist attack–can affect the course of parliamentary discussion. For instance, think of how a new government often goes to some trouble to seem different to the one they replace, or how events such as the 9/11 attacks altered government priorities.

In this paper we examine text records of what was said in the Australian Federal Parliament. We create a dataset based on all sitting days from 1901 through to 2017. This means that we have records for 7,869 days in the House of Representatives and 6,682 days in the Senate, although we drop a handful of days for various reasons. Our dataset consists of counts of every word that occurs at least thrice, after we convert all words to lowercase, remove numbers and punctuation, join commonly co-located words, and remove stop words.

We use a topic model that allows correlation between topics to reduce the dimensionality of our dataset. We then analyse the topics using a Bayesian hierarchical Dirichlet model to examine changes at various types of events. These events include: changes in

government; elections; changes in economic conditions; and other significant events such as the 9/11 attacks.

We find: 1) changes in government tend be associated with topic changes even when the party in power does not change. For instance, the change from Hughes to Bruce in 1922, Menzies to Holt in 1966; Hawke to Keating in 1991; and Rudd to Gillard in 2010 are all associated with significant changes in topics despite no change in the party in power. 2) As expected, elections where the party in power also changes, such as Whitlam in 1972, Hawke in 1983, Howard in 1996, Rudd in 2007, and Abbott in 2013 are associated with topic changes, but the 2001 and 2004 Howard re-elections stand out as elections where the government was returned yet there was a significant change in topics. 3) Economic events, such as financial crises, have less significant and persistent effects than other events such as terrorist attacks. **[More here on that one.] [Do we have different slopes that we could talk about?]**

Our work contributes to a growing modern quantitative social sciences literature that considers text as an input to more traditional methods, rather than requiring separate analysis. The advantage of using our analysis model is that it: allows the events to have more-complicated autocorrelated functional forms; allows us to implement pooling across groups of similar documents; and it identifies outlying topic distributions without the need to pre-specify the event of interest. The main weakness of this approach is that it does not appropriately propagate uncertainty and future models should improve on this. As the digitisation of historical sources continues and computational power becomes cheaper, we expect interest in this approach to only increase.

2 Data

2.1 Parliamentary text data

Following the example of the UK a daily text record called Hansard of what was said in the Australian Federal Parliament has been made available since it was established in 1901.[1] Earlier work on the influence of parliaments, such as Van Zanden, Buringh and Bosker (2012), often examined broader activity measures such as counts of sitting days. This allowed for long time-frames and wide comparisons. But analysing Hansard records and their equivalents directly is increasingly viable as new methods and reduced computational costs make it easier.

The recent digitisation of the Canadian Hansard, Beelen et al. (2017), allowed Rheault and Cochrane (2018) to examine ideology and party polarisation in Britain and Canada. In the UK, Duthie, Budzynska and Reed (2016) analysed Hansard records to examine which politicians made supportive or aggressive statements toward other politicians between 1979 and 1990 and Peterson and Spirling (2018) examined polarisation. And as digitisa-

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[1]While Hansard is not necessarily verbatim, it is considered close enough for text-as-data purposes. For instance, Mollin (2008) found that in the case of the UK Hansard the differences would only affect specialised linguistic analysis. Edwards (2016) examined Australia, New Zealand and the UK, and found that changes were usually made by those responsible for creating the Hansard record, instead of the parliamentarians. As those who create Hansard are tasked with creating an accurate record of proceedings, this suggests the records should be fit for the purpose of our analysis.

tion methods improve older UK records can be analysed, for instance Dimitruk (2018) considers the effect of estate bills on prorogations in seventeenth century England. In New Zealand, Curran et al. (2017) modelled the topics discussed between 2003 and 2016, and Graham (2016) examined unparliamentary language between 1890 and 1950. And in the US Gentzkow, Shapiro and Taddy (2018) examined congressional speech records from 1873 to 2016 to find that partisanship has risen in the past few decades.

Parts of Australian Hansard records have been analysed for various purposes. For instance, Rasiah (2010) examined Hansard records for the Australian House of Representatives to examine whether politicians attempted to evade questions about Iraq during February and March 2003. And Gans and Leigh (2012) examined Australian Hansard records to associate mentions by politicians of certain public intellectuals with neutral or positive sentiment.

The Australian Federal Parliament makes daily Hansard records available online as PDFs and these are considered the official release. Additionally, XML records are available in some cases.[2] We detail the sources of our Hansard PDFs in A.1 and Appendix A.2 provides an example of what a Hansard PDF looks like. There are 14,551 days worth of publicly available Hansard records across both chambers of the Australian Federal Parliament. Our data cleaning process indicates concerns with a small number of PDFs and these are detailed in Appendix A.3.

The formatting of the Hansard records changes over time. We use scripts written in R (R Core Team (2018)) to convert the PDFs into daily text records. An example of the workflow and some reduced-detail scripts are provided in Appendix A.4. Some error is introduced at this stage because many of the records are in a two-column format that need to be separated, and the PDF parsing is not always accurate especially for older records. An example of the latter issue is that 'the' is often parsed as 'thc'. These errors are corrected when they occur more than twice and can be identified.

The percentage of stop-words in each record is reasonably consistent over time. This suggests that there is no significant difference in the quality of the parsing over time. Details of this check are provided in Appendix A.5. We use Hansard records on a daily basis in this paper. We pre-process our text before applying a topic model. The specific steps that we take are to: remove numbers and punctuation; change the words to lower case; and concatenate multiword names titles and phrases, such as new zealand to new_- zealand. Then the sentences are deconstructed and each word considered individually.

3   Model

The goal of our modeling strategy is twofold. Firstly, we want to use topic modeling (Blei, Ng and Jordan, 2003) to summarise the Hansard text into meaningful topics, which reduce the dimensionality of the text data and capture the main themes discussed in parliament over time. Secondly, we want to relate the resulting topic distributions to temporal

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[2]Tim Sherratt makes these XML records available as a single download and also presents them in a website (http://historichansard.net/) that can be used to explore Commonwealth Hansard records from 1901 to 1980. Commonwealth XML records from 1998 to 2014 are available from Andrew Turpin's website, and from 2006 through to today from Open Australia's website. The records can also be downloaded from the Australian Hansard website.

trends, changes and events, such as governement changes, elections, and other external events.

We use a Correlated Topic Model (CTM) Blei and Lafferty (2007) to obtain estimated topic distributions over time. We consider these topic distributions as reduced dimension inputs that can be analysed within another model. We then formulate a Bayesian hierarchical Dirichlet model to assess changes in the topic distributions in relation to events of interest. In Appendix B, we include an alternative approach that follows Taddy (2015) by using word2vec, which more closely uses words, rather than topics, as an input.

In the following sections, we describe both the topic modeling approach and the Bayesian hierarchical analysis model. Firstly, we describe the Latent Dirichlet Allocation (LDA) model (Blei, Ng and Jordan, 2003), before moving on the CTM, which is a natural extension of LDA. We then discuss the Bayesian hierarchical Dirichlet analysis model used to investigate changes in topics.

3.1 Latent Dirichlet Allocation

Although more- or less-fine levels of analysis are possible, here we are primarily interested in considering a day's topics. This means that each day's Hansard record needs to be classified by its topics. Sometimes Hansard records includes titles that make the topic clear. But not every statement has a title and the titles do not always define topics in a well-defined and consistent way, especially over longer time periods. One way to get consistent estimates of the topics discussed in Hansard is to use the LDA method of Blei, Ng and Jordan (2003).[3]

The key assumption behind the LDA method is that each day's text, 'a document', in Hansard is made by speakers who decide the topics they would like to talk about in that document, and then choose words, 'terms', that are appropriate to those topics. A topic could be thought of as a collection of terms, and a document as a collection of topics, where these collections are defined by probability distributions. The topics are not specified *ex ante*; they are an outcome of the method. In this sense, this approach can be considered unsupervised machine learning. Terms are not necessarily unique to a particular topic, and a document could be about more than one topic. This provides more flexibility than other approaches such as a strict word count method. The goal is to have the words found in each day's Hansard group themselves to define topics.

As applied to Hansard, the LDA method considers each statement to be a result of a process where a politician first chooses the topics they want to speak about. After choosing the topics, the speaker then chooses appropriate words to use for each of those topics. More generally, the LDA topic model works by considering each document as having been generated by some probability distribution over topics. Similarly, each topic could be considered a probability distribution over terms. To choose the terms used in each document the speaker picks terms from each topic in the appropriate proportion. Figures 6 and 7 in Appendix C.1 illustrates an example with five topics, two documents, and ten terms.

Following Blei and Lafferty (2009), Blei (2012) and Griffiths and Steyvers (2004), the

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[3]For instance as implemented by the R `topicmodels` package of Grün and Hornik (2011).

process by which a document is generated is more formally considered to be:

1. There are $1, 2, \ldots, k, \ldots, K$ topics and the vocabulary consists of $1, 2, \ldots, V$ terms. For each topic, decide the terms that the topic uses by randomly drawing distributions over the terms. The distribution over the terms for the kth topic is β_k. Typically a topic would be a small number of terms and so the Dirichlet distribution with hyperparameter $\boldsymbol{\eta}$ is used: $\beta_k \sim \text{Dirichlet}(\boldsymbol{\eta})$, where $\boldsymbol{\eta} = (\eta_1, \eta_2, \ldots, \eta_K)$.[4] In practice, a symmetric Dirichlet distribution is usually used, where all elements of $\boldsymbol{\eta}$ are equal.

2. Decide the topics that each document will cover by randomly drawing distributions over the K topics for each of the $1, 2, \ldots, d, \ldots, D$ documents. The topic distributions for the dth document are θ_d, and $\theta_{d,k}$ is the topic distribution for topic k in document d. Again, the Dirichlet distribution with the hyperparameter $0 < \alpha < 1$ is used here because usually a document would only cover a handful of topics: $\theta_d \sim \text{Dirichlet}(\boldsymbol{\alpha})$. Again, strictly α is vector of length K of hyperparameters, but in practice each is usually the same value.

3. If there are $1, 2, \ldots, n, \ldots, N$ terms in the dth document, then to choose the nth term, $w_{d,n}$:

   a. Randomly choose a topic for that term n, in that document d, $z_{d,n}$, from the multinomial distribution over topics in that document, $z_{d,n} \sim \text{Multinomial}(\theta_d)$.
   b. Randomly choose a term from the relevant multinomial distribution over the terms for that topic, $w_{d,n} \sim \text{Multinomial}(\beta_{z_{d,n}})$.

Given this set-up, the joint distribution for the variables is (Blei (2012), p.6):

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D,1:N}, w_{1:D,1:N}) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(z_{d,n}|\theta_d) p\left(w_{d,n}|\beta_{1:K}, z_{d,n}\right) \right).$$

Based on this document generation process the analysis problem, discussed next, is to compute a posterior over $\beta_{1:K}$ and $\theta_{1:D}$, given $w_{1:D,1:N}$. This is intractable directly, but can be approximated (Griffiths and Steyvers (2004) and Blei (2012)).

After the documents are created, they are all that we have to analyse. The term usage in each document, $w_{1:D,1:N}$, is observed, but the topics are hidden, or 'latent'. We do not know the topics of each document, nor how terms defined the topics. That is, we do not know the probability distributions of Figures 6 or 7. In a sense we are trying to reverse the document generation process – we have the terms and we would like to discover the topics.

If the earlier process around how the documents were generated is assumed and we observe the terms in each document, then we can obtain estimates of the topics (Steyvers and Griffiths (2006)). The outcomes of the LDA process are probability distributions and

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[4]The Dirichlet distribution is a variation of the beta distribution that is commonly used as a prior for categorical and multinomial variables. If there are just two categories, then the Dirichlet and the beta distributions are the same. In the special case of a symmetric Dirichlet distribution, where all elements of $\eta = 1$, it is equivalent to a uniform distribution. If $\eta < 1$, then the distribution is sparse and concentrated on a smaller number of the values, and this number decreases as η decreases. A hyperparameter is a parameter of a prior distribution.

these define the topics. Each term will be given a probability of being a member of a particular topic, and each document will be given a probability of being about a particular topic. That is, we are trying to calculate the posterior distribution of the topics given the terms observed in each document (Blei (2012), p. 7):

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D,1:N} | w_{1:D,1:N}) = \frac{p(\beta_{1:K}, \theta_{1:D}, z_{1:D,1:N}, w_{1:D,1:N})}{p(w_{1:D,1:N})}.$$

Gibbs sampling or the variational expectation-maximization algorithm can be used to approximate the posterior. A summary of these approaches is provided in Appendix C.2. The choice of the number of topics, k, drives the results and must be specified *a priori*. If there is a strong reason for a particular number, then this can be used. Otherwise, one way to choose an appropriate number is to use cross validation.

One weakness of the LDA method is that it considers a 'bag of words' where the order of those words does not matter (Blei, 2012). It is possible to extend the model to reduce the impact of the bag-of-words assumption and add conditionality to word order. Additionally, alternatives to the Dirichlet distribution can be used to extend the model to allow for correlation. This motivates the use of the Correlated Topic Model, described in the next section.

3.2 Correlated Topic Model

As mentioned in the previous section, one of the limitations of LDA is that the model assumes that the presence of one topic is not correlated with the presence of another topic. Indeed, the corrleation between topics is not modeled or accounted for. However, in relaity, we would expect Hansard topics related the army may be more commonly found with topics related to the navy, but less commonly with topics related to banking. The goal of the CTM (Blei and Lafferty, 2007) is to account for this correlation between topics, in order to produce more realistic and stable topic distributions over time.

As with LDA, the process assumed to generate the documents is the key aspect as this will be reversed to estimate the topics. The document generation process of Blei, Ng and Jordan (2003) discussed earlier, is slightly modified. Rather than assuming that the distribution of topics in a document, θ_d, are a draw from a Dirichlet distribution, as in step 2 in LDA above, CTM assumes

$$\theta_d \sim \text{Logistic Normal}(\mu, \Sigma)$$

This is the main addition of CTM over LDA, in that it replaces the assumption of the Dirichlet distribution with a more flexible logistic Normal distribution, which incorporates a covariance structure across the topics. The remainder of the steps of the document generating process are identical to LDA.

However, the replacement of the Dirichlet distribution, which is conjugate to the multinomial, with the logistic Normal distribution adds a level of computational complexity to CTM. The posterior distributions of the parameters of interest ($\beta_{1:K}, \theta_{1:D}, z_{1:D,1:N}$) can no longer be obtained using standard simulation techniques such as Gibbs Sampling. Blei and Lafferty (2007) develop a fast variational inference procedure for estimating the CTM.

This estimation approach has also been extended by Roberts, Stewart and Airoldi (2016) as part of their work on Structural Topic Models.

Figure 1 illustrates an output of the CTM This illustrative example only shows five per cent of data from the House of Representatives between 1901 and 2017. It shows how each day's parliamentary discussion can be allocated to a topic and highlights how the prominence of these topics changes over time.
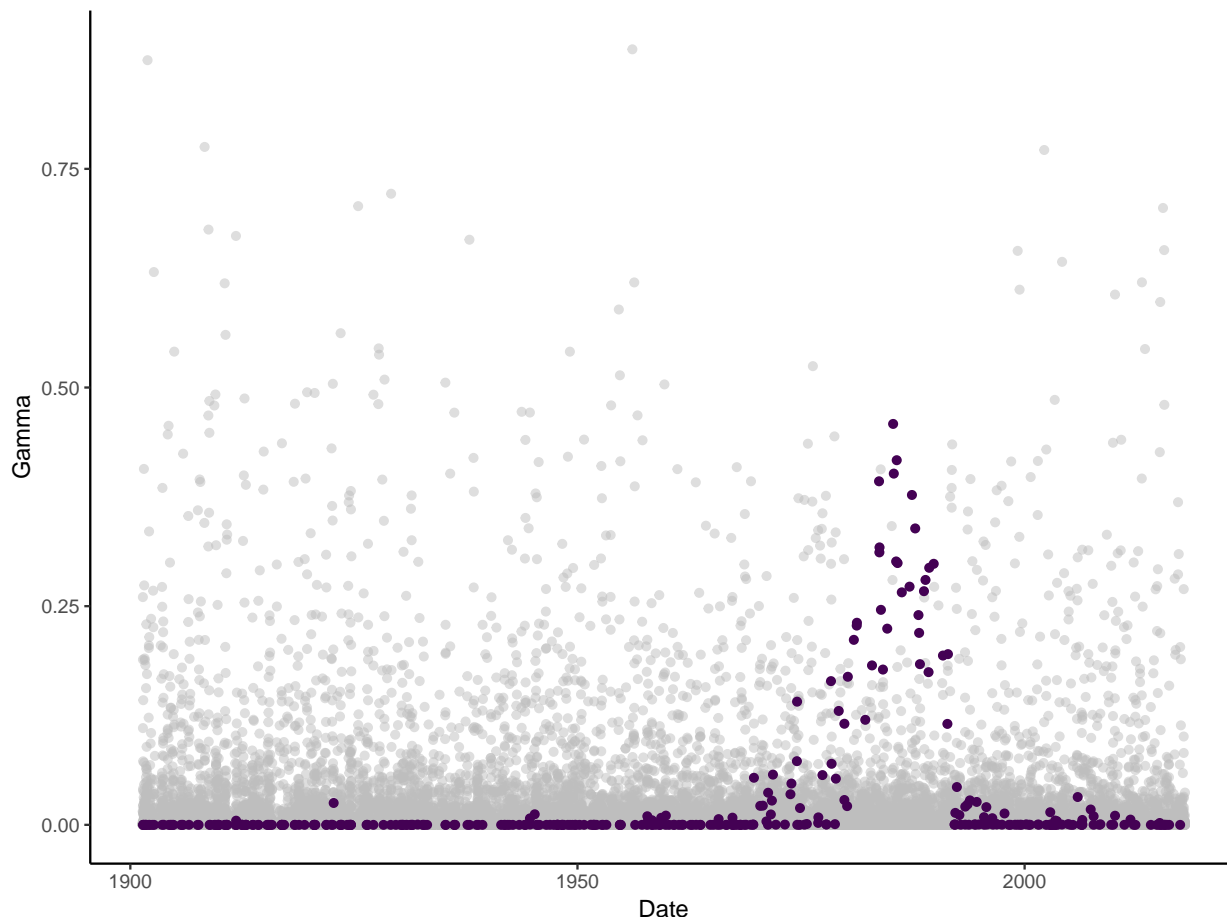

Figure 1: Illustrative topic model output, with Topic 17 highlighted

3.3 Analysis model

The main output of the CTM of interest is the proportion of each topic appearing in each document, that is, the θ_d. For the next stage of the modeling process, we are interested in how the distribution of topics changes in relation to different types of events. But with 40 topics for each of the roughly 14,551 **[UPDATE]** house-sitting-days the data are still too noisy to easily visualise changes around events.

One option for relating the topic distributions to events would be to use a Structural Topic Model (STM) (Roberts, Stewart and Airoldi, 2016). The distinguishing aspect of the STM is that it considers more than just a document's content when constructing topics.

For example, we may believe a document's author, or the time at which it was written, or, in the case of Hansard, the government or election period, may affect the topics within that document. The STM allows this additional information, or meta-data, to affect the construction of topics, though influencing either topical prevalence or topical content. The assumption that there is some document generation process is the same as the LDA method, it is just that this process now includes metadata.

Consider a matrix of covariates X_d, where each column relates to a different covariate or aspect of the meta-data, and the row refers to document d value of each covariate. Similar to the CTM, the STM assumes the topics within a document θ_d are a draw from a logistic Normal distribution with mean μ. However, the STM framework assumes that the mean parameter is a linear function of covariates X_d:

$$\theta_d | X_d \gamma \Sigma \sim \text{Logistic Normal}(\mu = X_d \gamma, \Sigma)$$

The STM framework with covariates could theoretically allow the relationships between topics and certain types of events to be assessed. For example, one covariate within the model could be the government g that was in power during the time corresponding to document d. However, there are several limitations to the STM covariate framework in relation to our goal of assess the relationship between topics and events:

- There is no way of specifying more complicated autocorrelated functional forms of the effects of events over time. For example, we believe that the effect of an election would peak at the time of the election, then gradually decay as a function of days since election. In the STM framework, it is possible to specify constant or linear effect of elections over time, or a spline relationship over elections, but it is not possible to restrict the effect of a specific election over time to be monotonically decreasing.
- There is no way of implementing partial pooling across groups of similar documents. The STM framework assumes that documents are independently and identically distributed conditional on the covariates in the model. However, it could be expected that topic distributions within a particular government period, for example, may be more or less likely to contain certain topics for reasons that are not reflected in the topic prevalence covariates. To account for this, we would like a covariate model that allows for the partial pooling of variance in topic distributions by group, such as sitting period.
- There is no way of identifying 'outlying' topic distributions – and therefore events that had an important effect – without pre-specifying the event of interest in the model. For example, if we think that the 9/11 terrorist attacks had an effect on parliamentary discourse, a dummy for 9/11 would have to be included in the STM framework. Ideally, we would like to identify important events based on different-to-expected topic distributions, after accounting for time trends, government and election effects.

To overcome these challenges, we formalize a statistical framework which allows us to systematically identify significant changes in topic distributions over time. Specifically, we use the estimated topic distributions from CTM described in the previous section as an

input into a Bayesian hierarchical Dirichlet regression framework, which relates proportions of each topic to underlying time trends, changes in goverments and elections. This set-up also allows us to identify 'outlying' topic distributions and relate these to other, non-scheduled political events.

Define θ_{dp} to be the proportion of topic of topic p on day d. Note that the $\theta_{d,1:P}$ for $p = 1, 2, \ldots P = 40$ are equal to the estimated values of θ_d from the CTM. We assume that the majority of variation in topics is across sitting periods s, where a sitting period is defined as any group of days that are less than one week apart. Using this definition, there are a total of 745 sitting periods across all years of interest (1901–2017).

The topic proportions on day d are modeled in reference to their membership in a particular sitting period s. Firstly, we assume that each distribution of topics, $\theta_{d,1:P}$ for each day is a draw from a Dirichlet distribution with mean parameter $\mu_{s[d],1:P}$:

$$\theta_{d,1:P} \sim \text{Dirichlet}(\mu_{s[d],1:P})$$

where the notation $s[d]$ refers to the sitting period s which day d belongs to. This distributional assumption accounts for the fact that on any given day, the sum of all proportions in each topic must equal 1.

The goal of the model is to relate these proportions to the government g of time d, and also the days since the most recent election, e, while account for underlying time trends. The mean parameters μ_{sp} are modeled on the log scale as

$$\log \mu_{s,p} = \alpha_{g[s],p} + \cdot \alpha_{e[s],d,p} + \sum_{k=1}^{K} \beta_{p,k} \cdot x_{s,k} + \delta_{s,p}$$

where:

- $\alpha_{g[s],p}$ is the mean effect for government g (which covers sitting period s) and topic p
- $\alpha_{e[s],d,p}$ is the effect of election e (which occurs in sitting period s) for topic p on day d since the election
- $\sum_{k=1}^{K} \beta_{p,k} \cdot x_{s,k}$ is the underlying time trend, modeled using splines: $x_{s,k}$ is the kth basis spline in sitting period s, and $\beta_{p,k}$ is a cofficient on the kth basis spline.
- $\delta_{s,p}$ is a structured random effect for each sittiing period and topic.

The government term $\alpha_{g[s],p}$ assumes there is some underlying mean effect of each government on the topic distribution. We place uninformative priors on each of these parameters:

$$\alpha_{g[s],p} \sim N(0, 100)$$

The election term $\alpha_{e[s],d,p}$ assumes there is an initial effect of an election on the topic distribution, which then decays as a function of days since election, d. In particular, we model this as an AR(1) in d:

$$\alpha_{e[s],d,p} = \rho_{e[s],p} \cdot \alpha_{e[s],d-1,p}$$

The value of the initial effect $\alpha_{e[s],0,p}$ and the AR(1) term ρ both have non-informative priors:

$$\alpha_{e[s],0,p} \sim N(0, 100)$$

$$\rho_{e[s],p} \sim U(0, 1)$$

We model the underlying time trend in topics using splines regression. The intuition behind this term is to capture the underlying non-linear trend in topic distributions over time, which is caused by large-scale structural changes in the economy, and Australian society and culture. The $x_{s,k}$ for $k = 1, 2, \ldots K$ are the value of cubic basis splines for sitting period s at knot point k. We chose to place knot points every 5 sitting periods as this is the average length of time for a government to sit (**CHECK**). Non-informative priors are placed on the splines coefficients:

$$\beta_{p,k} \sim N(0, 100)$$

Finally, the sitting period-specific random effect $\delta_{s,p}$ allows for the topic distributions in some sitting periods to be different than expected based on the government/election effects. This allows us to identify large deviations away from the expected distribution, thus helping to identify the effect of other, non-government and non-election events. In addition, this set up also partially pools effects across sitting periods. The $\delta_{s,p}$'s are modeled as

$$\delta_{s,p} \sim N(0, \sigma^2_{e[s],p})$$

The variance parameters $\sigma^2_{e[s],p}$ give an indication of the how the variation in topics is changing over election periods. If the estimates of the variance are larger, then there is more variation in the topics discussed within an election period. Non-informative priors are placed on the variance parameters:

$$\sigma_{e[s],p} \sim U(0, 3)$$

We run the model in Stan using the `RStan` package of Stan Development Team (2018). **An illustration of the validity of our analysis model using simulated data is in Appendix E.**

4 Results

We are interested in considering the effect of various events on what is talked about in the Australian Federal Parliament. Political events are those related to a change of government or an election. Other events are defined by substantial changes in various economic measures, such as the onset of the Great Depression or floating the currency; events of a historical magnitude, such as entering into a war or the 9/11 attacks; or events that had a significant effect on Australian life, such as hosting the Olympics, or the Mabo decision. The full list of events that we consider are detailed in Appendix D.

First considering the mean topic distributions over governments, Figures 2 - 4.

Topics related to Federation such as the British Empire and the constitution decrease in importance over time. A substantial increase in the importance of issues dealing with
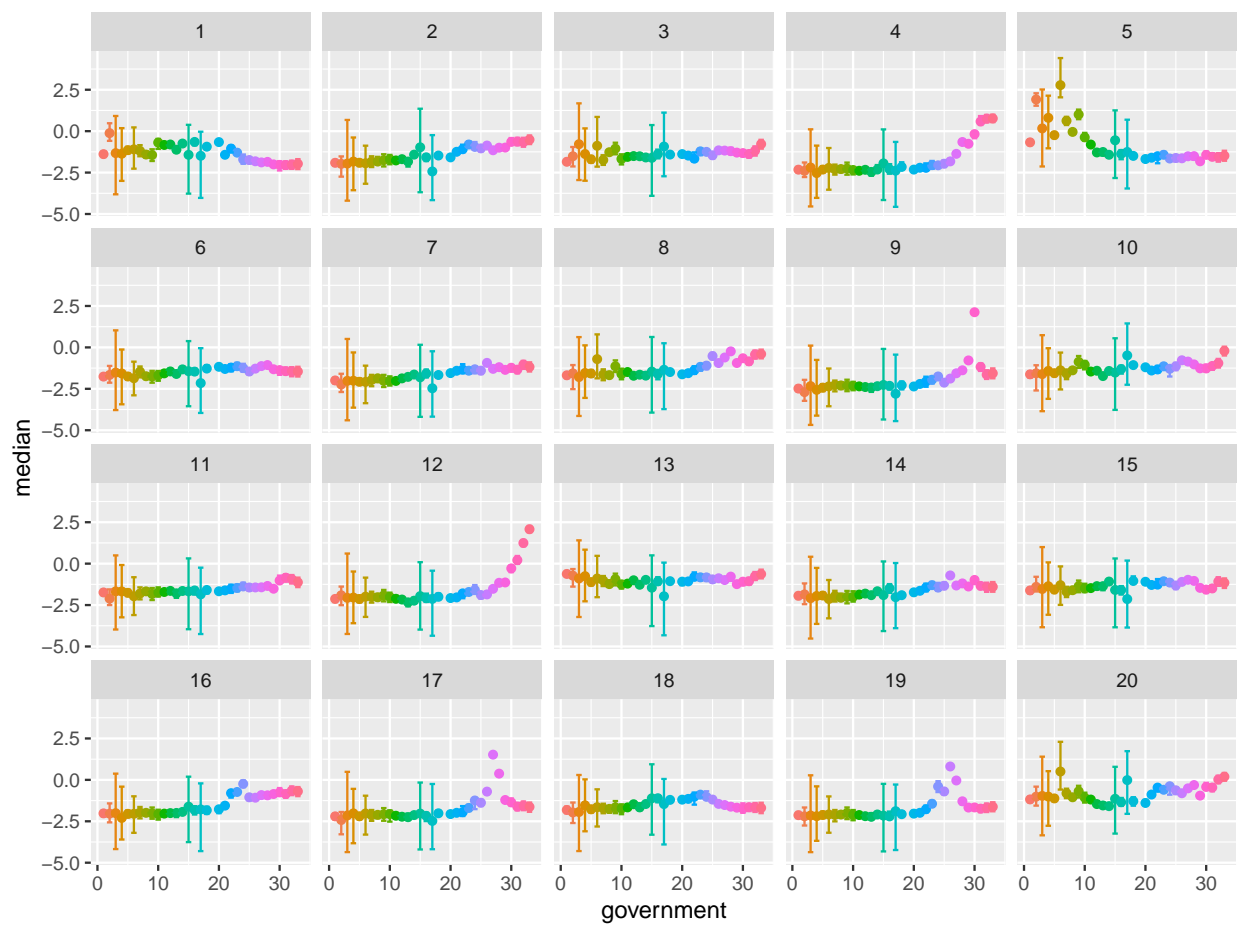
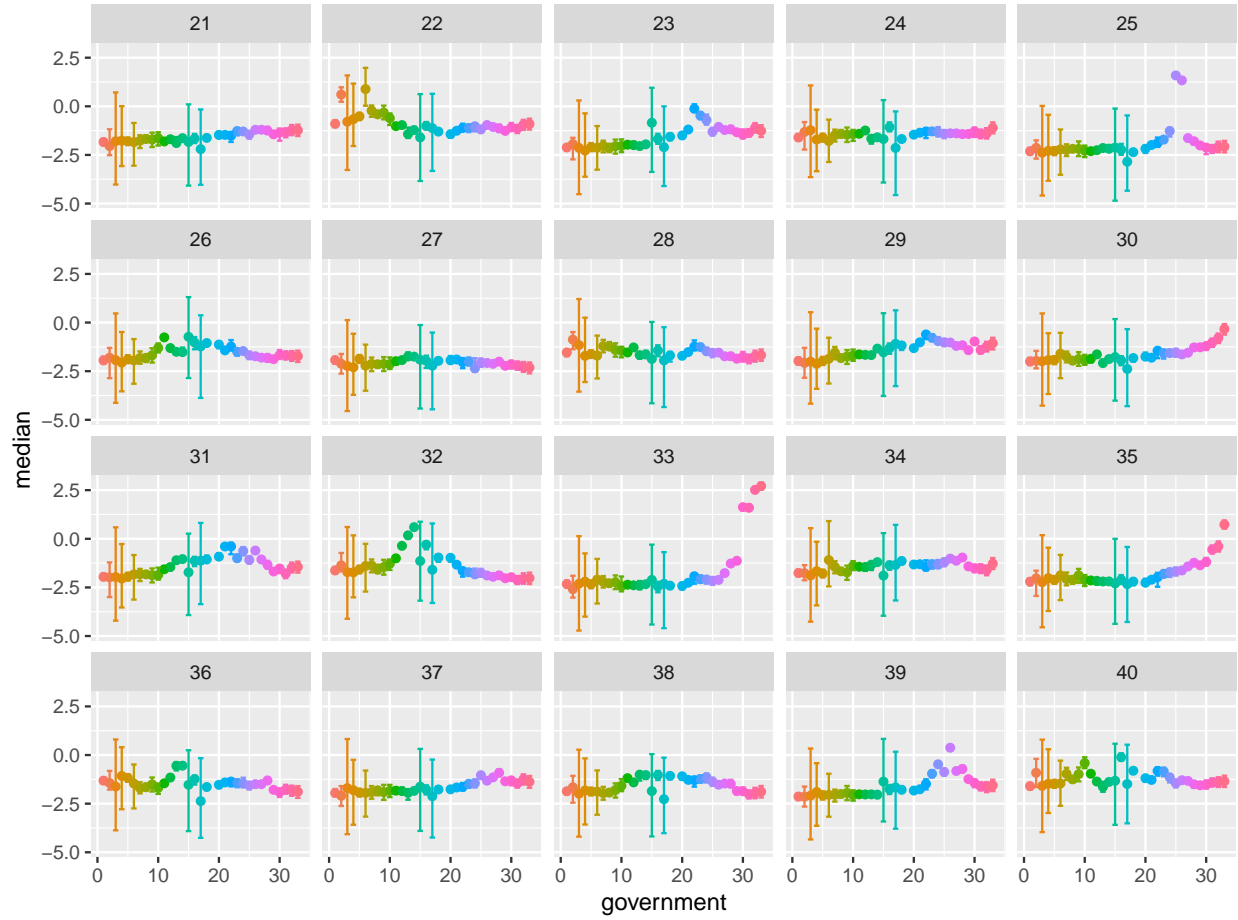Figure 2: Illustrative topic model output, with Topic 17 highlighted

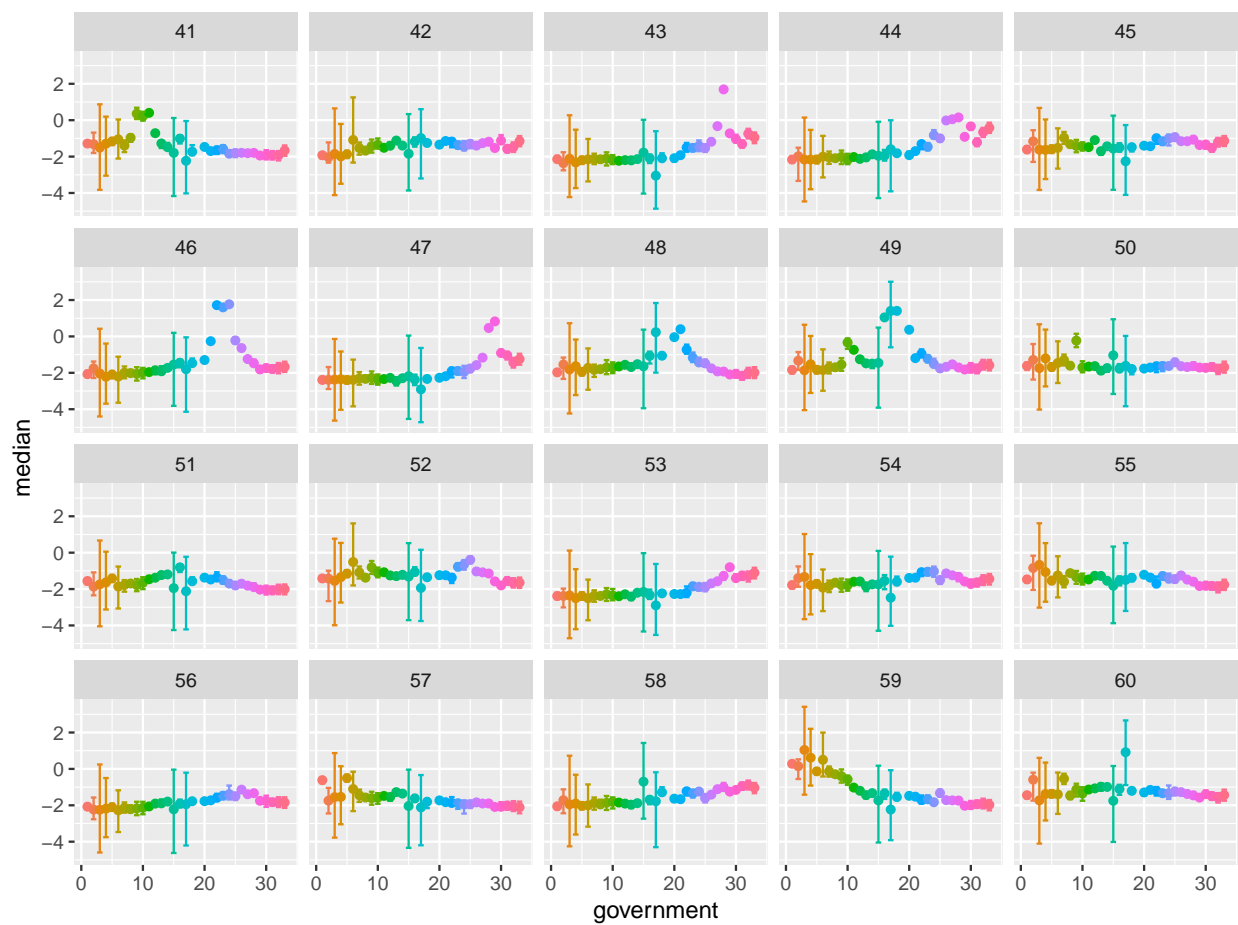Figure 3: Illustrative topic model output, with Topic 17 highlighted

Figure 4: Illustrative topic model output, with Topic 17 highlighted

Increasing from 20th gov: 2, 4, 8, 12,
32 increases and then decreases
Increases only recently: 33, 35
Breakpoint: 23, 25, 49, 48, 46, 47, 41

Figure **??** shows the grouping by election. If elections had significant effects on the discussion in parliament then there would be considerable change between groups. However changes generally appear to be longer-term rather than election to election.

Groupings by government. This can be different to election groupings, for instance, the change from the Rudd to Gillard governments happened without an election. Similarly, John Howard's three terms are all considered the one government for our purposes.

Here we see much more difference between adjacent events. This suggests that new governments tend to talk about different topics than the government they replace.

For instance, all of the incrementing variables have a significant effect on the prevalence of Topic 1. Table 1 shows that this has to do with tariffs and trade. On the other hand, Topic 2 has to do with aspects of daily life such as community and children, and Topic 3 has to do with legal issues and neither is significant. This is not surprising given the centrality of these concerns at all times.

5 Summary and conclusions

In this paper we examined what was said in Australia's parliaments. We downloaded and parsed PDFs for Australian states and federal parliaments. We then used a text model to group the discussions into topics and analysed the effect of various events on the distribution of the discussion.

In general we found that changes in government changed the distribution of topics discussed in parliament, but that elections did not. We found that significant events such as 9/11 had substantial and lasting changes, but that with certain exceptions, economic events did not.

Text analysis has well-known biases and weaknesses and is a complement to more detailed analysis such as qualitative methods and case studies. We consider the results presented in this paper, as well as many of those results of the larger text-as-data research program, as fitting within findings based on other methods.

While using text as data has well-known shortcomings, it allows larger-scale analysis that would not be viable using less-automated approaches and so it can identify patterns that may otherwise be overlooked.

Add discussions about weakenss of the model.

Add other discussion that I thought of and now forget.

Table 1: Top words for each topic

topic	terms
1	life, representatives, death, parliament, respect
2	constitution, parliament, rights, powers, constitutional
3	public, prime_minister, public_servants, time, accounts
4	bank, money, country, per_cent, budget
5	children, family, women, parents, marriage
6	tax, income, taxation, treasurer, per_cent
7	party, prime_minister, country, leader, time
8	department, service, officers, office, estimates
9	vote, electoral, election, voting, party
10	court, law, royal, evidence, attorneygeneral
11	transport, roads, road, shipping, ships
12	war, defence, country, ill, soldiers
13	industry, trade, countries, development, country
14	question, department, services, answer, staff
15	late, loss, lost, bay, sympathy
16	question, notice, department, report, information
17	security, time, world, war, country
18	world, british, nations, countries, country
19	per_cent, tariff, ad, wine, val
20	land, territory, northern_territory, railway, capital
21	housing, million, increase, budget, expenditure
22	war, country, matter, production, time
23	defence, time, national, service, vietnam
24	time, budget, tax, billion, million
25	tariff, duty, industry, per_cent, duties
26	amendments, committee, time, provisions, section
27	money, amount, financial, treasurer, revenue
28	question, time, regard, desire, learned
29	education, schools, students, school, university
30	oil, energy, industry, nuclear, research
31	industrial, union, workers, court, arbitration
32	industry, wheat, wool, growers, farmers
33	per_cent, budget, time, tax, business
34	committee, parliament, time, report, parliamentary
35	community, time, health, support, local
36	per_cent, wul, governments, commission, country
37	pension, health, medical, pensioners, scheme
38	per_cent, petitioners, petition, parliament, governments
39	health, services, funding, care, million
40	clause, provision, committee, section, proposed

Table 2: Hansard sources and notes

Parliament	URL
Commonwealth	aph.gov.au/parliamentary_business/hansard
Queensland	parliament.qld.gov.au/work-of-assembly/hansard
New South Wales	parliament.nsw.gov.au/hansard/Pages/Hansard-API.aspx
Victoria	parliament.vic.gov.au/hansard
Tasmania	parliament.tas.gov.au/HansardArchive/
South Australia	hansardpublic.parliament.sa.gov.au/#/search/1
Western Australia	parliament.wa.gov.au/hansard/hansard1870to1995.nsf/vwWeb1870Main
Australian Capital Territory	hansard.act.gov.au/hansard/downyear.htm
Northern Territory	parliament.nt.gov.au/business/parliamentary-records

A   Hansard details

A.1   *Hansard sources*

Hansard records are available from a variety of sources, as detailed in Table 2.
    Detail where from, and which years are being used and why.
    Which years are being used (not non-OCRd)

A.2   *Example Hansard page*

Figure 5

A.3   *Known Hansard issues*

The NSW Legislative Council was established earlier than 1856, however the earlier Hansard records have not been through an independent OCR process and were not used in this paper. However, the Google Tesseract OCR engine as implemented by Ooms (2018*b*) provided useful data and these could be used in the future.
    Which PDFs are missing or have no content, etc.
    Notes: Positive means I am missing some, Negative means I have too many. Source: https://www.aph.gov.au/Parliamentary_Business/Statistics/Senate_StatsNet/General/sittingdaysyear

A.4   *Example Hansard PDf to text record workflow*

Example of the workflow from PDF to text
    These scripts are primarily based on: the PDFtools package of Ooms (2018*a*); the tidyverse package of Wickham (2017); the tm package of Feinerer and Hornik (2018); the lubridate package of Grolemund and Wickham (2011); and the stringi package of Gagolewski (2018).
    The functions of those packages are supported by: the furrr package of Vaughan and Dancho (2018); and the tictoc package of Izrailev (2014).
    The hunspell package of Ooms (2017) is also used to help find spelling issues.

days ago, to the effect that the South Australian Government do not intend to charge preferential rates upon their railways after the 1st February, is correct?

Sir WILLIAM LYNE.—I have received no definite information upon the subject from the South Australian Government. I forwarded a communication to the Minister for Railways in South Australia in reference to these rates some time ago, and his reply was to the effect that the South Australian Government desired to, as far as possible, assimilate the rates for the produce of all the States, but that up to the present time, although there had been several conferences upon the subject, they had been unsuccessful, and that he had requested the Railways Commissioner to report further. I had another telegram or letter to-day, which I have not by me now, but it does not carry the matter much further.

PAPER.

Mr. DEAKIN laid upon the table—

Minute by the Prime Minister to His Excellency the Governor-General, relating to the contract for supplies for troops in South Africa.

SYDNEY TELEGRAPHIC BUSINESS.

Mr. THOMSON.—Is the Minister who represents the Postmaster - General yet in possession of a return which has been promised by the Government, showing the lengths of telegrams sent in one day from the Sydney and suburban offices?

Mr. DEAKIN.—I mentioned the matter to my honorable colleague, Sir Philip Fysh, and he told me that he proposed to inform the honorable member that he had received a return, but that, thinking it was not quite in compliance in all particulars with the honorable member's request, he referred it back to have further information added. He is expecting to receive the return again at any moment.

Mr. JOSEPH COOK.—Will the Government keep back the consideration of the Postal Rates Bill until the return has been presented to the House?

Mr. DEAKIN.—I shall call the attention of the Postmaster-General to the honorable member's wish.

QUARANTINE ADMINISTRATION.

Mr. MAHON asked the Prime Minister, *upon notice—*

1. Has his attention been drawn to complaints concerning the administration by State Governments of the quarantine laws and regulations?

House of Representatives.

Thursday, 6 February, 1902.

Mr. SPEAKER took the chair at 2.30 p.m., and read prayers.

PUNCHING AND SHEARING MACHINES.

Mr. R. EDWARDS.—I should like to know from the Minister for Trade and Customs whether, as the amendment of the honorable and learned member for Corio, placing various machines and tools of trade upon the free list, was carried, the Government are prepared to exempt punching and shearing machines.

Mr. KINGSTON.—I think that the fair construction of the determination arrived at by the committee yesterday necessitates the exemption of punching and shearing machines, and the Government therefore propose to admit them duty free from to-day.

SOUTH AUSTRALIAN PREFERENTIAL RAILWAY RATES.

Mr. THOMAS.—I wish to ask the Minister for Home Affairs if the report which appeared in the newspapers a few

Table 3: Missing days

year	HoR PDFs	Senate sitting days	HoR sitting days	HoR difference
1902	106	93	107	1
1908	93	84	91	-2
1909	97	71	98	1
1918	87	68	86	-1
1920	113	76	114	1
1921	92	79	93	1
1934	36	22	35	-1
1935	54	37	55	1
1942	44	36	45	1
1948	89	39	90	1
1951	55	40	56	1
1955	53	36	52	-1
1974	64	64	62	-2
1985	65	74	66	1
1991	66	83	67	1
1992	60	76	44	-16
1993	47	53	46	-1
1994	69	80	68	-1
1995	71	78	70	-1
1997	79	82	76	-3
1998	56	57	54	-2
2000	71	71	73	2
2002	68	60	69	1
2003	74	64	75	1
2004	58	49	59	1
2012	63	57	67	4

In addition to the packages already mentioned, in this step the R scripts to do this use the `tidytext` R package of Silge and Robinson (2016).

And Benoit (2018) for compounding multiword expressions.

A.5   *Stopwords over time*

Insert graph of stop words over time.

B word2vec alternative

An alternative approach that follows Taddy (2015).

C   Topic modelling example and details

C.1   Examples

For instance, if there were five topics and two documents, then the first document may be comprised mostly of the first few topics; the other document may be mostly about the final few topics (Figure 6).
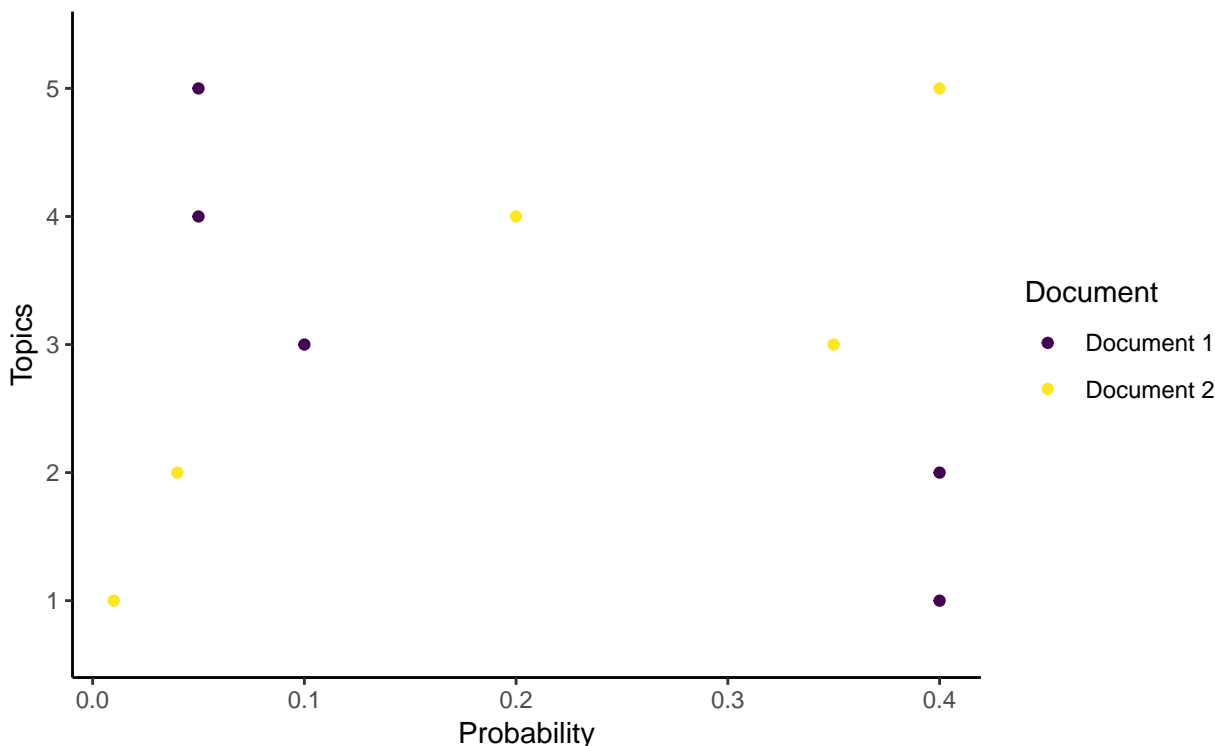

Figure 6: Probability distributions over topics for two documents

For instance, if there were ten terms, then one topic could be defined by giving more weight to terms related to immigration; and some other topic may give more weight to terms related to the economy (Figure 7).

C.2   Posterior estimation

Following Steyvers and Griffiths (2006) and Darling (2011), the Gibbs sampling process attempts to find a topic for a particular term in a particular document, given the topics of all other terms for all other documents. Broadly, it does this by first assigning every term in every document to a random topic, specified by Dirichlet priors with $\alpha = \frac{50}{K}$ and $\eta = 0.1$ (Steyvers and Griffiths (2006) recommends $\eta = 0.01$), where α refers to the distribution over topics and η refers to the distribution over terms (Grün and Hornik (2011), p. 7). It then selects a particular term in a particular document and assigns it to a new topic based on the conditional distribution where the topics for all other terms in all
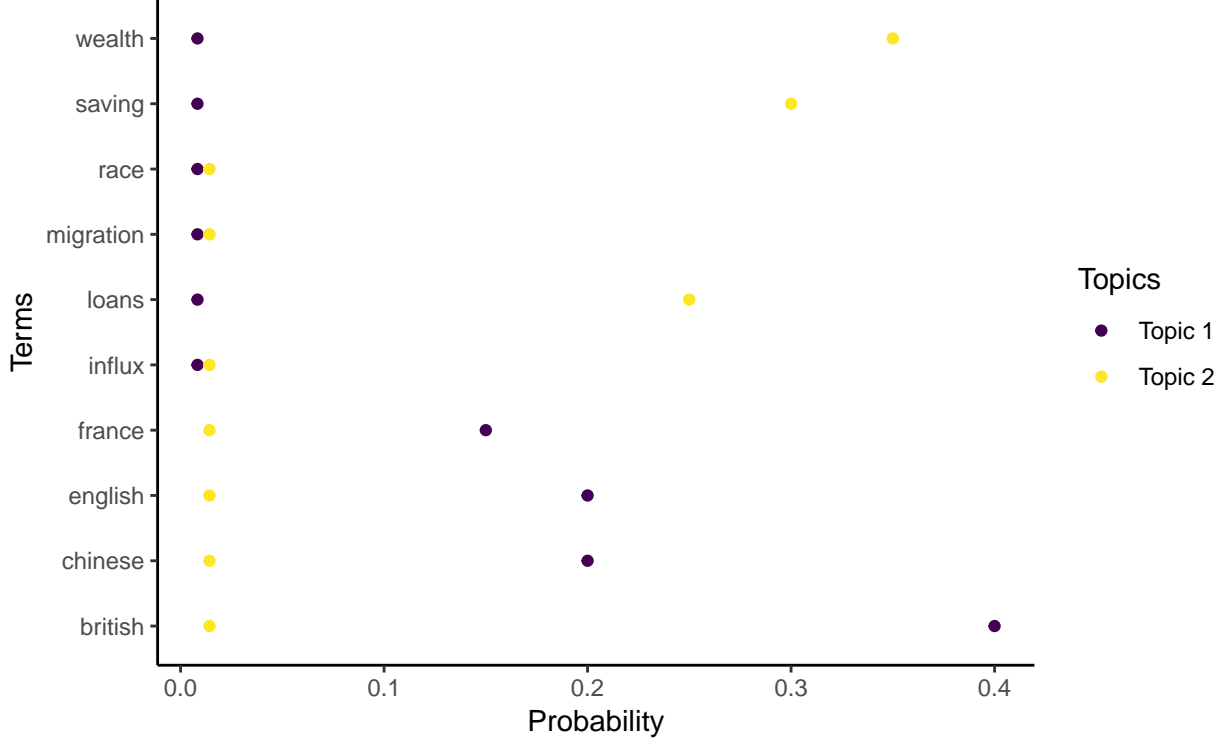
Figure 7: Probability distributions over terms

documents are taken as given ([Grün and Hornik](2011), p. 6):

$$p(z_{d,n} = k | w_{1:D,1:N}, z'_{d,n}) \propto \frac{\lambda'_{n \to k} + \eta}{\lambda'_{. \to k} + V\eta} \frac{\lambda'^{(d)}_{n \to k} + \alpha}{\lambda'^{(d)}_{-i} + K\alpha}$$

where $z'_{d,n}$ refers to all other topic assignments; $\lambda'_{n \to k}$ is a count of how many other times that term has been assigned to topic k; $\lambda'_{. \to k}$ is a count of how many other times that any term has been assigned to topic k; $\lambda'^{(d)}_{n \to k}$ is a count of how many other times that term has been assigned to topic k in that particular document; and $\lambda'^{(d)}_{-i}$ is a count of how many other times that term has been assigned in that document. Once $z_{d,n}$ has been estimated, then estimates for the distribution of words into topics and topics into documents can be backed out.

This conditional distribution assigns topics depending on how often a term has been assigned to that topic previously, and how common the topic is in that document ([Steyvers and Griffiths](2006)). The initial random allocation of topics means that the results of early passes through the corpus of document are poor, but given enough time the algorithm converges to an appropriate estimate.

C.3   Selection of number of topics

[TBD]

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C.4 Robustness of results

[IS THIS BEING USED?] Here we change the number of sitting days considered either side of an event. The results in the main section of the paper are for the nearest ten days either side of an event. Here are show that the results are essentially the same if the nearest one, two, five, and twenty days either side of an event.

D Events

For background on the Premiers' Plan see Copland (1934).
For background on the Gruen tariff cut see Gruen (1975).
Add the graphs and procedures.

Table 4: Change in governments

government	primeMinister	party	start	end	diedInOffice
Barton	Edmund Barton	Protectionist	1901-01-01	1903-09-24	No
Deakin 1	Alfred Deakin	Protectionist	1903-09-24	1904-04-27	No
Watson	Chris Watson	Labour	1904-04-27	1904-08-18	No
Reid	George Reid	Free Trade	1904-08-18	1905-07-05	No
Deakin 2	Alfred Deakin	Protectionist	1905-07-05	1908-11-13	No
Fisher 1	Andrew Fisher	Labour	1908-11-13	1909-06-02	No
Deakin 3	Alfred Deakin	Commonwealth Liberal	1909-06-02	1910-04-29	No
Fisher 2	Andrew Fisher	Labor	1910-04-29	1913-06-24	No
Cook	Joseph Cook	Commonwealth Liberal	1913-06-24	1914-09-17	No
Fisher 3	Andrew Fisher	Labor	1914-09-17	1915-10-27	No
Hughes	Billy Hughes	Labor, National Labor and Nationalist	1915-10-27	1923-02-09	No
Bruce	Stanley Bruce	Nationalist (Coalition)	1923-02-09	1929-10-22	No
Scullin	James Scullin	Labor	1929-10-22	1932-01-06	No
Lyons	Joseph Lyons	United Australia (Coalition)	1932-01-06	1939-04-07	Yes
Page	Earle Page	Country (Coalition)	1939-04-07	1939-04-26	No
Menzies 1	Robert Menzies	United Australia (Coalition)	1939-04-26	1941-08-28	No
Fadden	Arthur Fadden	Country (Coalition)	1941-08-28	1941-10-07	No
Curtin	John Curtin	Labor	1941-10-07	1945-07-05	Yes
Forde	Frank Forde	Labor	1945-07-06	1945-07-13	No
Chifley	Ben Chifley	Labor	1945-07-13	1949-12-19	No
Menzies 2	Robert Menzies	Liberal (Coalition)	1949-12-19	1966-01-26	No
Holt	Harold Holt	Liberal (Coalition)	1966-01-26	1967-12-19	Yes
McEwen	John McEwen	Country (Coalition)	1967-12-19	1968-01-10	No
Gorton	John Gorton	Liberal (Coalition)	1968-01-10	1971-03-10	No
McMahon	William McMahon	Liberal (Coalition)	1971-03-10	1972-12-05	No
Whitlam	Gough Whitlam	Labor	1972-12-05	1975-11-11	No
Fraser	Malcolm Fraser	Liberal (Coalition)	1975-11-11	1983-03-11	No
Hawke	Bob Hawke	Labor	1983-03-11	1991-12-20	No
Keating	Paul Keating	Labor	1991-12-20	1996-03-11	No
Howard	John Howard	Liberal (Coalition)	1996-03-11	2007-12-03	No
Rudd 1	Kevin Rudd	Labor	2007-12-03	2010-06-24	No
Gillard	Julia Gillard	Labor	2010-06-24	2013-06-27	No
Rudd 2	Kevin Rudd	Labor	2013-06-27	2013-09-18	No
Abbott	Tony Abbott	Liberal (Coalition)	2013-09-18	2015-09-15	No
Turnbull	Malcolm Turnbull	Liberal (Coalition)	2015-09-15	2018-08-24	No
Morrison	Scott Morrison	Liberal (Coalition)	2018-08-24	NA	NA

Table 5: Elections

year	electionDate	electionWinner
1901	1901-03-29	Non-labor
1903	1903-12-16	Non-labor
1906	1906-12-12	Non-labor
1910	1910-04-13	Labor
1913	1913-05-31	Non-labor
1914	1914-09-05	Labor
1917	1917-05-05	Non-labor
1919	1919-12-13	Non-labor
1922	1922-12-16	Non-labor
1925	1925-11-14	Non-labor
1928	1928-11-17	Non-labor
1929	1929-10-12	Labor
1931	1931-12-19	Non-labor
1934	1934-09-15	Non-labor
1937	1937-10-23	Non-labor
1940	1940-09-21	Non-labor
1943	1943-08-21	Labor
1946	1946-09-28	Labor
1949	1949-12-10	Non-labor
1951	1951-08-28	Non-labor
1954	1954-05-29	Non-labor
1955	1955-12-10	Non-labor
1958	1958-11-22	Non-labor
1961	1961-12-09	Non-labor
1963	1963-11-30	Non-labor
1966	1966-11-26	Non-labor
1969	1969-10-25	Non-labor
1972	1972-12-02	Labor
1974	1974-05-18	Labor
1975	1975-12-13	Non-labor
1977	1977-12-10	Non-labor
1980	1980-10-18	Non-labor
1983	1983-03-05	Labor
1984	1984-12-01	Labor
1987	1987-07-11	Labor
1990	1990-03-24	Labor
1993	1993-03-13	Labor
1996	1996-03-02	Non-labor
1998	1998-10-03	Non-labor
2001	2001-11-10	Non-labor
2004	2004-10-09	Non-labor
2007	2007-11-24	Labor
2010	2010-08-21	Labor
2013	2013-09-07	Non-labor
2016	2016-07-02	Non-labor

Table 6: Key events

theDate	event	expected
1901-01-01	Federation	Yes
1902-05-31	Second Boer War ends	Yes
1907-11-08	Harvester case	No
1910-09-10	Australian pound introduced	Yes
1914-07-28	World War I starts	No
1918-11-11	World War I ends	Yes
1929-10-29	Black Tuesday Stock Market Crash	No
1931-06-11	Premiers' Plan agreed	Yes
1932-05-13	Jack Lang dismissed as NSW Premier	Yes
1939-09-01	World War II starts	Yes
1945-09-02	World War II ends	Yes
1949-10-17	Snowy Hydro construction begins	Yes
1956-11-22	Melbourne Olympics	Yes
1962-08-03	Australia enters Vietnam War	Yes
1966-02-14	Decimalisation	Yes
1972-12-02	Australia exits Vietnam War	Yes
1973-01-18	Gruen tariff cut	Yes
1973-10-20	White Australian Policy ended	Yes
1975-11-11	The Dismissal	No
1983-12-12	Australian dollar is floated	Yes
1984-02-01	Medicare establised	Yes
1987-10-19	Black Monday Stock Market Crash	No
1990-08-27	State Bank of Victoria collapse	No
1991-02-10	State Bank of South Australia collapse	No
1992-06-03	Mabo decision	No
1996-03-28	Port Arthur massacre	No
1996-12-23	Wik decision	No
1999-09-20	INTERFET deployment begins	No
2000-07-01	GST introduced	Yes
2000-09-15	Sydney Olympics	Yes
2001-09-11	9/11 attack	No
2002-10-12	Bali bombings	No
2008-09-15	Lehman Brothers bankruptcy	No

E   Analysis model

Here we illustrate the validity of our analysis model using simulated data.

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