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Similarities and Differences in the Argumentative Characteristics of the Official Brexit Campaigns

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1. Introduction

This paper aims to better understand the nature of dialogue surrounding the UK's vote to leave the European Union. Specifically, to uncover differences in argumentative structure between the two official campaigns[1]—Vote Leave (VL) and Britain Stronger in Europe (BSE). Designated by the Electoral Commission on the 13th April 2016, `Vote Leave Ltd' and `The In Campaign Ltd' received a range of benefits, including an increased spending limit; one free distribution of information to voters; referendum campaign broadcasts; and the use of certain public rooms (Electoral Commission 2016).

Argumentative text has two components: what information the author is trying to convey, and in what style this information is conveyed. Hence, this paper uses a series of text analysis methods to analyse variation in *focus* and *sentiment* between these two campaigns. First, to examine campaign focus, two automated tools are employed to cluster text into distinct themes or topics — a structural topic model and a thematic[2] analysis of elementary contexts. By incorporating document-level covariates (or "tags"), these clusters can be used to examine how dialogue varied between the campaigns and hence uncover information regarding their relative strategies. Using these two algorithmically distinct, yet similar approaches, helps to (1) uncover more underlying information held within the corpus by utilising each method's unique strengths; and (2) act as a robustness check. By conducting multiple automated content analyses on the same corpus and identifying structures that re-emerge, we can be more confident that outputs are a result of the data's structure rather than methodological choice (Sanders et al. 2017). Then, using surveys conducted by

[1] Throughout this paper, the term "campaign" will refer to the official designated campaigns unless stated otherwise. Someone's "camp", on the other hand, may refer to whether that individual or organisation wanted to remain a part of or leave the European Union.

[2] While this paper refers to these methods as "thematic", elsewhere it is also referred to as keyword-in-context, or KWIC (Illia et al. 2014)

YouGov, the congruency of public opinion and campaign focus is briefly examined.

Second, this paper builds upon work which explores social media sentiments in the build up to the referendum (Lansdall-Welfare et al. 2016, Cortina Borja et al. 2016, Howard & Kollanyi 2016, Hänska & Bauchowitz 2017). By utilising the `sentimentr` package, this paper studies how sentiment[3] (or "polarity") varies between the official campaigns. Beyond a purely academic exercise, the analysis of campaign sentiment became a major talking point during and after the referendum, with particularly notable colloquialisms including both "Project Fear" – first coined by Rob Shorthouse during the 2014 Scottish Independence Referendum to describe the "Better Together" campaign, the phrase was later assigned to BSE (Iain 2016) — and "remoaners" (Borrelli 2017). Fear and moaning typically embody negative sentiment, and I can test whether the campaigns' distributions of sentence-level polarity scores differ in their mean or variance given a number of assumptions.

A clear thematic divide exists between the camps. BSE employed a predominantly focussed approach by concentrating their resources on economics, jobs and small businesses. VL on the other hand undertook a scattershot approach by spreading their resources across a broader range of policy areas while maintaining a common unpinning on maximising British sovereignty. A correspondence analysis shows little reciprocity for the majority of issues — one exception being public services, which acted as a key battleground. These findings are reinforced across methodologies. By comparing these results with various survey responses, I conclude that the broader-based approach of VL mobilised a larger proportion of the electorate despite the economy being an influential issue.

An analysis of sentiment yielded two observations. First, the variability in sentence-level polarity scores was not significantly different between the two campaigns, suggesting both campaigns were equally consistent in expressing their chosen sentiment. Second, the mean sentence-level polarity score was significantly

[3] In this context, sentiment analysis is the process by which a researcher aims to establish how positive or negative a segment of text is. For example, "this food is bad" may be interpreted as negative, "this food is great" as positive, and "this food is okay" as neutral. More context-specific dictionaries can be employed to interpret the polarity of sentences in scenarios where standard dictionaries may be inadequate – i.e. when aiming to understand financial market sentiment.

higher for BSE than VL. This result continued to hold when varying a number of parametric assumptions, and implies that the remain campaign's website content was significantly more positive than its leave counterpart.

2. Data

The dataset contains all plain text from the official campaign websites (Vote Leave Ltd 2016, The In Campaign Ltd 2016). This includes all text directly hosted on the website, as well as all third-party newspaper articles, studies, speeches, and statements that are linked directly from the official websites and are written by a figure recognised as affiliated with the given campaign. It is reasonable to assume that this information accurately captures the discourse of the official campaigns during the EU referendum, or at least mirrors their key talking points. Each webpage, whether hosted on the website or elsewhere, constitutes a single document in our analysis and hence can vary considerably in length. Every document is assigned a list of covariates ("tags") which outline some basic document-level information about the text. The most crucial covariate for testing our hypotheses is the camp to which the document belongs ("leave" or "remain"). For completeness, the role of the author ("campaign staff", "MP", "Peer", etc), the date of publication[4], and the style of the text ("newspaper article", "study", "speech", etc) were also detailed at the document-level. Due to the corpus' heterogenous nature, these additional tags have little substantive use beyond control variables.

3. Structural Topic Model (STM)

The STM was introduced by Roberts et al. (2013), and builds off traditional topic models such as the Latent Dirichlet Allocation (LDA) (Blei et al. 2003), and the Correlated Topic Model (CTM) (Lafferty & Blei 2006). The STM is a generative model: its algorithm defines a random data-generation process for each document, and then observed word frequencies are used to find the most likely values for the model's parameters. The STM generates a number of topics (as defined by the user) that are

[4] For many of the archived sources, the date of publication was not publicly available and hence this covariate was designated as NA. Due to a high proportion of documents being labelled this way, a time series analysis would likely have been fruitless.

conceived as joint probability functions over documents and words. Similarly, to other topic models such as the LDA, a single topic is defined as a mixture of words where each word has a probability of belonging to a given topic. A document is itself a mixture over topics, meaning that a single document can be composed of multiple different topics depending on its constituent words.

The STM differentiates itself by allowing the researcher to incorporate document-level meta-data (Roberts et al. 2015). Each document is assigned a list of covariates (as defined in Section 2), allowing the user to study relationships between these covariates and topics. Specifically, topical content refers to the rate of word use within a given topic, while topical prevalence refers the proportion of a document devoted to a given topic. Topical content is used for identifying the hidden semantic structures within the documents, while topical prevalences are used for analysing the relationships between topics and meta-data. We will use both of these approaches to further our understanding of campaign dialogue.

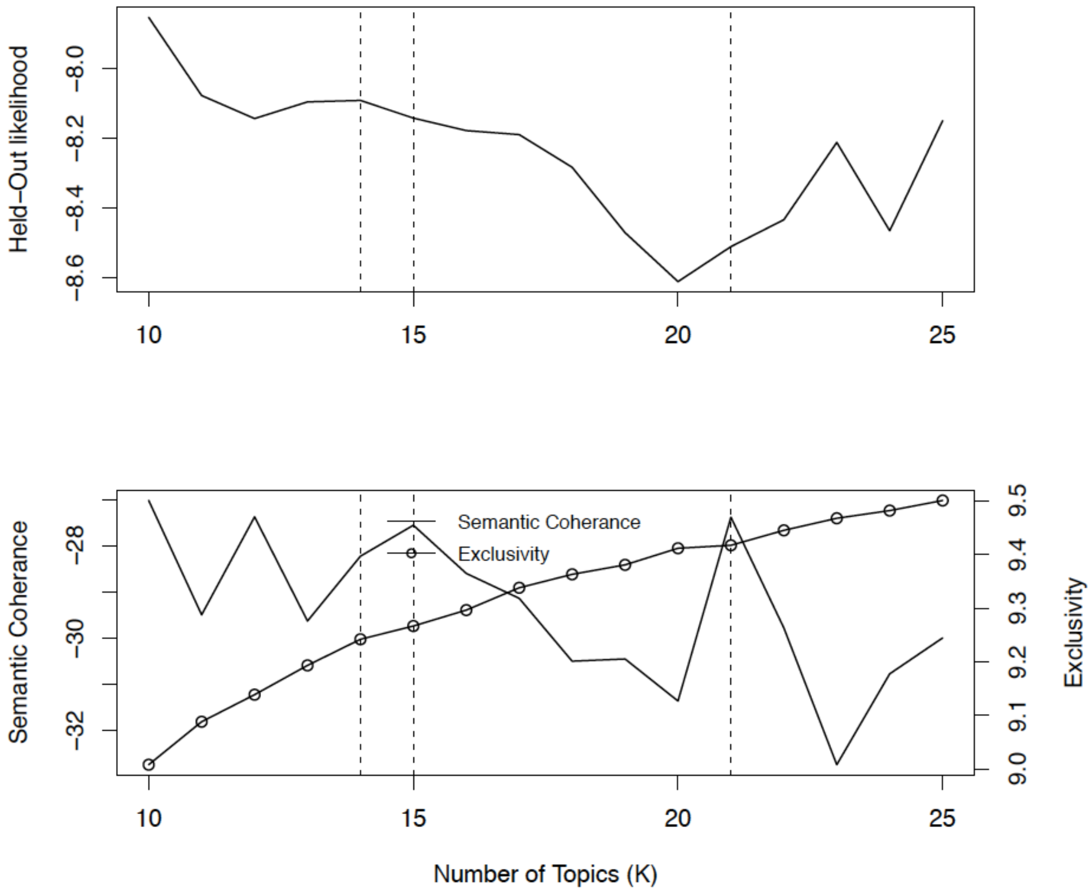
3.1 Model Selection

The STM is an unsupervised method that requires the researcher to designate the number of topics (or "K" value) used in the estimation. The STM package for R (Roberts et al. 2017) provides a number of useful metrics for choosing the most suitable value of K. The first is the "held-out likelihood estimation" (Wallach et al. 2009), which is the estimated probability of words appearing in a document after those words have been intentionally removed during the estimation step. The idea of this method is to find the number of topics which produces a model that can better explain the left-out set of words. The second is known as "semantic coherence". Developed by Mimno et al. (2011), it is maximised when the most probable words in a given topic frequently co-occur with one another in the text, and correlates well with the human judgment of topic quality. The final method of analysing topic quality is the exclusivity of words to topics, measured using the FREX metric (Roberts et al. 2016). There is no best number of topics to designate in an estimation, and these three metrics should only advise the researcher on a series of K values to study in more depth.

Appendix A shows the value of these three measures over a broad number of K values ranging from 5 to 100. Using these results, one can pinpoint a smaller number of

K values to analyse in more depth (designated as the grey area in Appendix A). *Figure 1* shows the held-out likelihood, semantic coherence, and exclusivity of estimations with integer K values between 10 and 25. Based on these statistics, I ran an estimation using 14, 15 and 21 topics and inspected the outputs. In the end, 14 and 15 topic estimations formed topics that were too general and lacked clearly defined substantive meaning. I will proceed with 21 topics.

Figure 1: Metrics measuring topic quality for K = 10, 11, …, 25



3.2 Topic Content

Once the estimation has converged, the researcher is provided with multiple sets of characteristic words for each topic, including: (1) highest probability; and (2) FREX words weighted by their overall frequency and how exclusive they are to the topic. As with all unsupervised clustering methods, it is now the responsibility of the researcher to assign meaning to these lists. I have assigned a short label to each topic which summarises the underlying semantic structure likely being uncovered by the STM. *Table 1* lists these labels alongside the top five most probable words for each topic.

There are three points to note. Firstly, some labels and most probable words in *Table 1* may not appear to correspond to one another. In that case, it is important to realise this is a small sample from one set of characteristic words. A more complete list of words for each topic is given in Appendix B. Secondly, the topic labelled “Climate Change and IOs*” contains an asterisk because its meaning is unclear. The most probable words include “world, leave, nato, european”, whereas the most frequent words include “nato, gas, energi, electr”. The topic was very general, but appeared to be picking up the ideas of international cooperation and climate change. Finally, the topic “(Discussion)” was formed from a series of words relating to the nature of the discourse — it was not a substantive topic but rather is formed as a result of the source data being argumentative and emotional.

Table 1: Topic Labels for 21 topic STM

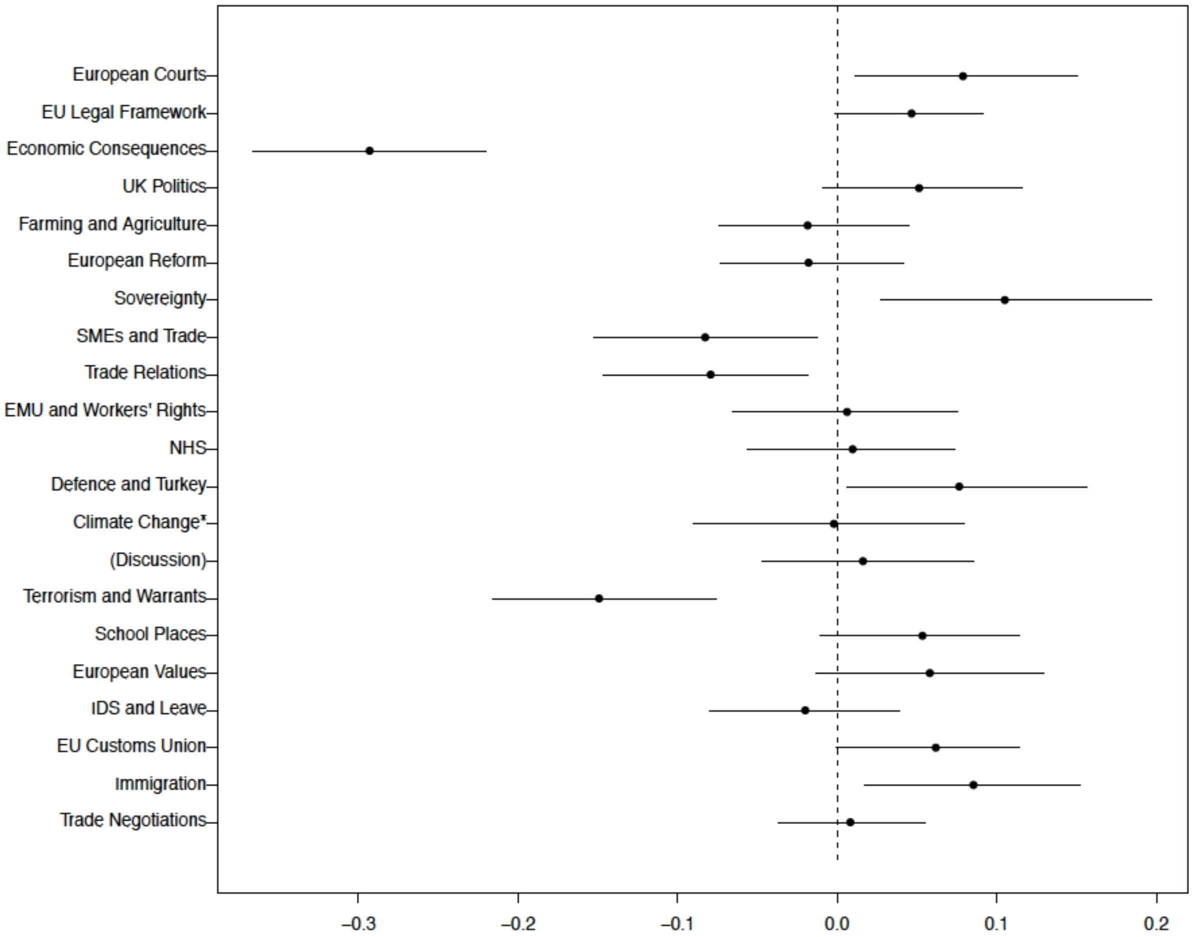
Topic	Label	Top 5 most probable words
1	European Courts	european countri court control govern
2	EU Legal Framework	european deal court chang govern
3	Economic Consequences	trade famili job busi mean
4	UK Politics	gove vote say law britain
5	Farming and Agriculture	farmer must make fine farm
6	European Reform	countri vote make fundament reform
7	Sovereignty	control can nhs vote take
8	SMEs and Trade	busi market small trade singl
9	Trade Relations	europ britain leav agreement market
10	EMU and Workers’ Rights	union european right countri want
11	NHS	leav vote nhs billion money
12	Defence and Turkey	european union defenc govern control
13	Climate Change and IOs*	world leav nato european can
14	(Discussion)	peopl thing think can britain
15	Terrorism and Warrants	european leav arrest britain economi
16	School Places	vote school leav place countri
17	European Values	countri european now chang peopl
18	IDS and Leave	said border leav duncan european
19	EU Customs Union	rule cost busi singl market
20	Immigration	immigr peopl control vote migrat
21	Trade Negotiations	trade agreement deal free negoti

3.3 Topic Prevalence

Having assigned meaning to the topic content, I can study the relationship between covariates and topics by isolating the differences in topic prevalence across the “leave” and “remain” tags. The STM allows the researcher to estimate the conditional probability of observing a particular topic in the text given some covariate being present. *Figure 2* shows the difference in the conditional probability of observing a given topic in the text across the camp dimension. Topics with a significantly negative (at the 10% level) difference are those more likely to occur in documents tagged with the "remain" covariate, and vice versa.

Figure 2 illustrates stark differences in topic prevalence. BSE focussed disproportionately on economics and business orientated arguments, demonstrated through their focus on the topics: "Economic Consequences", "SMEs and Trade", and "Trade Relations". They also focussed on arguments surrounding "Terrorism and Warrants" more than their counterpart.

Figure 2: Difference estimation across camp



On the other hand, Vote Leave focussed on a more diverse set of arguments, incorporating: "European Courts", "Sovereignty", "Defence and Turkey", and "Immigration". These topics seem unrelated in nature, however all but "Defence and Turkey" fall under the umbrella of judicial and legislative sovereignty. The remaining topic likely addresses the fear of Turkey's ascension to the EU and subsequent repercussions to the UK's security and immigration.

These results do not consider the overall proportions of the corpus associated with each topic. Rather the difference in the prevalence of those topics between documents tagged with the "leave" and "remain" covariates. This means that topics like the NHS, that despite there being no statistically significant difference across camp, may still have been a highly discussed topic.

4. T-Lab

T-LAB is a proprietary text analysis application (Lancia 2017). It provides the researcher with a number of options to modify the analysis to better fit the research question. This paper will utilise the software to cluster documents using a thematic analysis of elementary context units (ECUs), and use these "themes" to spatially analyse the relationship between ideas and tagged covariates in a correspondence analysis. These results will build upon, and provide a robustness check to, the STM findings.

4.1 Thematic Analysis of ECUs

T-LAB takes your input documents, and divides these into a number of short sentences or paragraphs known as elementary context units (ECUs). Each ECU has the same series of tagged covariates as the parent document, and are clustered in the thematic analysis of ECUs. As with the STM, we will be conducting an unsupervised (or "bottom up" approach).

T-LAB creates a matrix of ECUs and lexical units (words from the dictionary that reach a given frequency threshold) with presence/absence values. This matrix is normalised by using TF-IDF and taking the Euclidean norm of the row vectors. This allows for the clustering of context units using a not centred version of Principle Direction Divisive Partitioning (PDDP) (Boley 1998) to select the seeds for each K-means bisection. A contingency table of lexical units by clusters is formed, and a chi-squared test is applied to all the intersections[5].

[5] For more methodological information, see Lancia (2012).

To understand the meaning of these clusters (or "themes") the researcher is provided with the most characteristic words and context units ranked by their chi-squared value. The resulting class labels are presented in *Table 2* along with the top five most characteristic lexical units for each topic.

Table 2: T-Lab class labels

Class	Label	Characteristic Lexical Units
1	Single Market Access and SMEs	market business single small rules
2	Immigration and Border Controls	immigration take back control zone border
3	UK Politics and Critiques of Incumbent	prime think type interview minister look
4	Negotiations, geopolitics, and EU Expansion	accession negotiation united resolve Turkish
5	Defence and NATO	defence civil common nato servant
6	Real Economy	job family camp remain role strongerin low expert
7	Pressure on Public Services	nhs population spend school number
8	EMU and Fiscal Integration	union political eurozone monetary reform
9	Intelligence, Anti-Terrorism, and Human Rights	criminal intelligence influence arrest charter
10	Power of European Courts	court law justice european bind

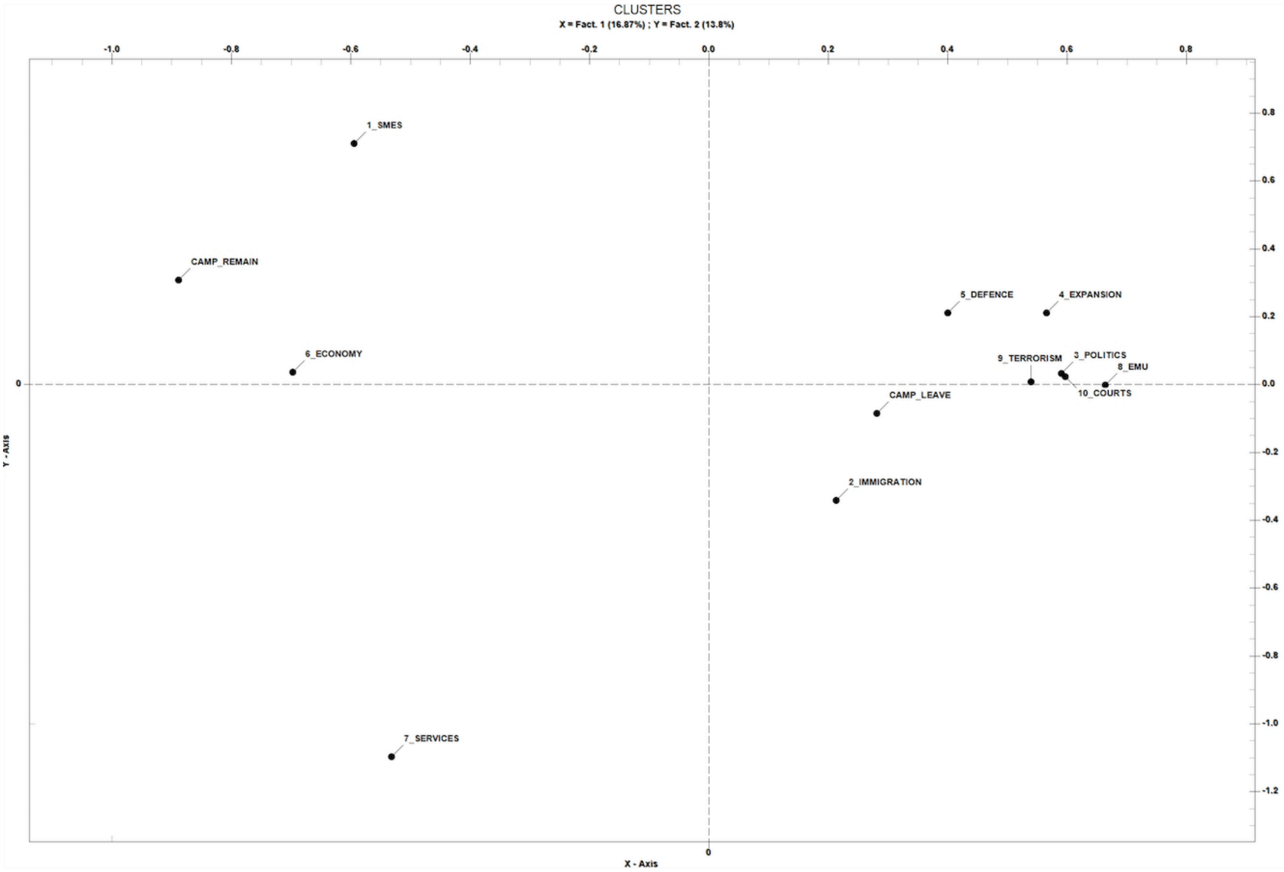
4.2 Correspondence Analysis

Once the thematic analysis of ECUs has produced a set of stable classes, T-LAB then conducts a correspondence analysis (CA) of the contingency table of lexical units by clusters. A CA provides a means of displaying or summarising a set of data in graphical form, a categorical alternative to principal component. In the context of T-LAB, the CA estimates a spatial relationship between clusters and covariates. As a variant of factorial analysis, it extracts a lower number of unobserved variables called factors with the property of summarising significant information. Each factor can be interpreted as a spatial dimension that is represented by an axis, so that tagged covariates on opposite factorial poles are the most weakly associated. As such, the positions of variables are contingent upon their associations rather than coordinates, with the distance reflecting the degree of co-occurrence. The first factorial dimension (x-axis graphically) aims to account for the maximum variation, and the second factorial dimension (y-axis graphically) aims to account for the maximum of remaining variation, and so on.

Hence, the total variation is divided into components along principal axes. In general, the dimensionality of the system is one less than the number of identified classes in the profile (Greenacre 1993). The CA is a framework for the researcher to formulate their own interpretation, rather than providing concrete significance.

T-LAB provides two ways to visualise the spatial relationships between classes in a correspondence analysis, a simple two-dimensional graph or a three-dimensional alternative. Evidently, the latter can account for a higher degree of variation due to the inclusion of an extra factorial axis, but in return one loses the ease of interpretation present in a two-dimensional graph. Schonhardt-Bailey (2010) explores this trade off in more detail with reference to the alternative proprietary text-analysis software "Alceste" (Reinert 1998). The added complexity of the three-dimensional graph is only necessary when it conveys additional information that cannot be inferred from its two-dimensional alternative. In our instance, the extra factor provides little additional understanding, and hence I will focus on the two-dimensional graph from *Figure 3*. *Figure 3* reinforces our findings from Section 3.3. The covariate "CAMP REMAIN" is strongly associated with themes of business and economy, whereas "CAMP LEAVE" is closely associated with a larger number of themes including defence, immigration and European expansion. This process of showing robustness through holding the data constant whilst varying the clustering methodology has allowed me to be more confident the output is a result of the underlying structures of dialogue, rather than purely methodological choice. This idea is explored fully by Sanders et al. (2017).

Figure 3: 2-Dimensional Correspondence Analysis Graph



The other interesting insight the CA provides is the position of the "Pressure on Public Services" cluster in relation to both camp tags. We find it positioned almost equidistant from both tags, suggesting that both campaigns focussed a roughly equal proportion of their available resources on this theme. However, the way both campaigns tackled this issue is likely different. By analysing the most characteristic ECU in theme 7 tagged with "CAMP LEAVE", and the most characteristic ECU tagged with "CAMP REMAIN", we can better understand the arguments put forward. These are displayed below respectively, all tags associated with each context unit are displayed at the top, and any characteristic lexical units are in bold.

****** *IDnumber 24 *ROLE-MP *TYPE- SPEECH *CAMP- LEAVE**

demographics meant that the **average household size** fell In recent **times** however **average household size** has changed little and the key factor driving the growth in **household numbers** has been **population** growth The total nonBritish net inflow of immigrants is close to 350000 with **migration** from the EU now accounting for about half of that figure The outcome of the recent renegotiation of benefits will

****** *IDnumber 44 *ROLE STRONGERIN *TYPE WEBSITE *CAMP REMAIN**
money for public services including the **NHS** and better **schooling** and healthcare for your family Leaving the EU would damage our economy and would force government **spending** cuts of 40 billion meaning less **money** for the NHS Source The Institute for Fiscal Studies and longer waiting **times** for operations GP appointments and AE treatment NHS England chief Simon Stevens says Brexit would be very

These characteristic ECUs demonstrate that despite equal proportions of resources being dedicated to theme 7 by both camps, the dialogue within the class is diverse. VL focussed on the impact of increased immigration from the European Union on the demand for public services, whereas BSE looked at how the economic costs could impact the Treasury's ability to continue funding public services. There are two things to note: (1) the way in which public services are being discussed is related to the central themes of both campaigns, economics versus sovereignty and immigration; and (2) it demonstrates that for the majority of themes, even for those that appear equally associated with both camps, campaign dialogue was not reciprocal and each group focussed on their specific areas of interest.

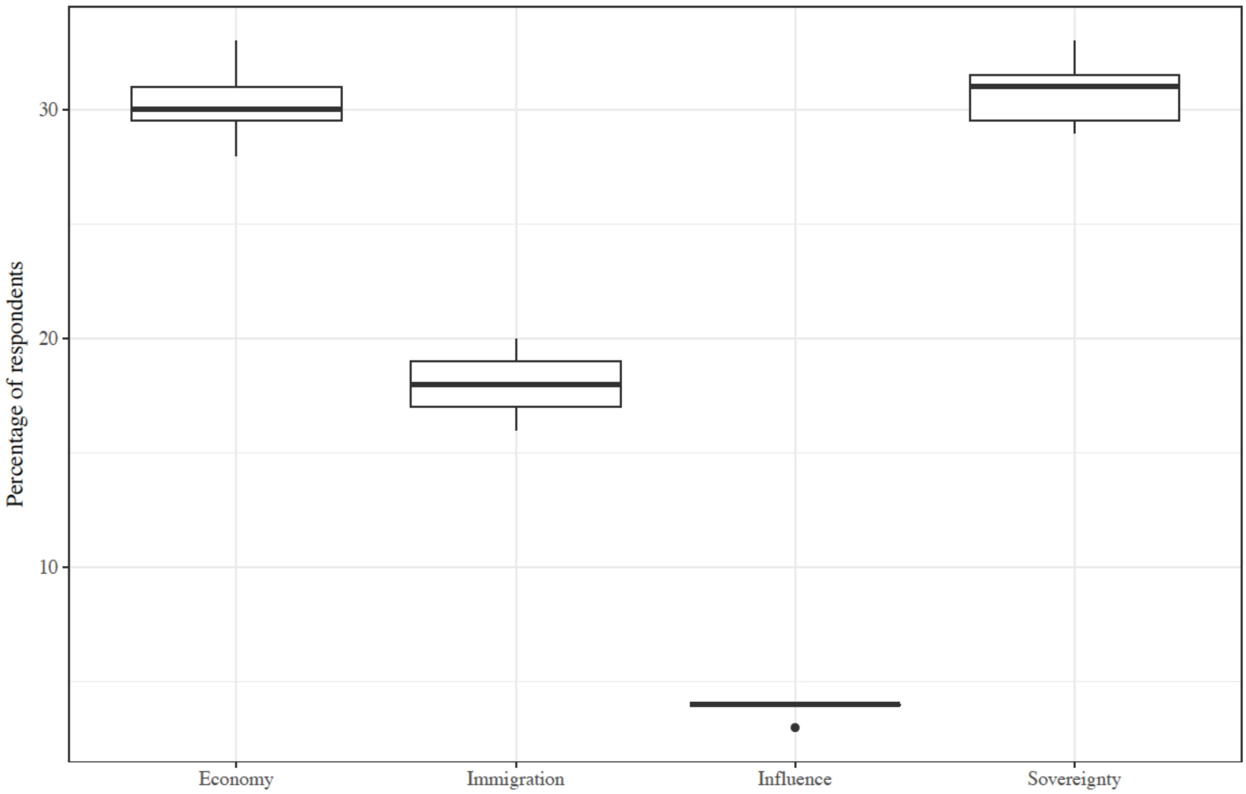
Both the STM and CA show that campaign dialogue was very polarised. BSE focussed predominantly on issues of economics and business, whereas VL spread their argument across a broader set of policies. The campaigns exhibited little to no reciprocity, that is, they did not address arguments outside of their main focus. Even with those topics which appear equally associated with both camps, a deeper analysis of characteristic context units reveals a continuation of the economics versus sovereignty divide. The use of two similar, yet independent, methods shows the robustness of these results.

5. YouGov Survey Analysis

In the months leading up to the referendum, YouGov surveyed the British public on their preferences regarding a range of referendum-related subjects. These subjects included their opinions of British politicians, their voting intentions in the upcoming referendum, and the perceived consequences of leaving the EU. The same questions were surveyed roughly fortnightly from February until 22nd June (the day before polling). By using the topics identified in Section 3 and 4, I can use survey responses as a signal for the potential effectiveness of each camp's approach. Campaigning decisions should be dependent upon the structure of public opinion, and hence a severe mismatch of the two may indicate an ineffective campaign.

Repeated throughout a large number of YouGov surveys was the following question: "Which ONE of the following will be most important to you in deciding how to vote in the referendum?". The respondents could choose answers from four areas: "which is likely to strike a better balance between Britain's right to act independently, and the appropriate level of co-operation with other countries"; "which is likely to be better for jobs, investment and the economy generally"; "which is likely to help us deal better with the issue of immigration"; and "which is likely to maximise Britain's influence in the world". From this point on, I will refer to these as sovereignty, economy, immigration and influence respectively. Respondents could also answer "something else" or "none of these"[6].

Figure 4: Survey responses on what is the most important issue when deciding how you vote in the referendum



[6] The difference between "something else" and "none of these" is unclear, they appear to imply the same thing. This contradiction is slightly baffling, and hence I ignore these options from here onward.

Figure 4 shows the percentages of respondents who chose each option in all surveys where the question was present. As demonstrated, responses stayed roughly consistent throughout the time period. The UK's economy and its sovereignty were the electorate's most poignant issues, with median percentages at 30% and 31% respectively. These two issues formed the backbone of BSE's and VL's websites and hence would lead to approximately equal numbers of targeted voters[7]. At around 18%, immigration was also an important topic for many voters. Analysis from Sections 3 and 4 revealed that immigration was more strongly associated with VL. As a result, VL may have been able to spread their reach to a larger proportion of the electorate than BSE. The statistics quoted in this section should be considered as descriptive, a causal explanation would require knowledge of the relative effectiveness of the two campaigns.

In sum, although BSE's focussed approach honed in on one of the most poignant issue for the electorate, VL's scattershot approach was able to draw on a much broader base whose aggregated proportion exceeded that of BSE.

6. Sentiment Analysis

The second characteristic of argumentative text is the way chosen information is conveyed to its audience. This can be done through webpage design, sentence structure, and other literary techniques. One of such method is the use of sentiment. Extensive research suggests the way an argument is phrased can significantly affect its persuasiveness – particularly the effect of negative (loss-based) arguments versus equivalent positive (gain-based arguments) arguments (Smith & Petty 1996, Kahneman & Tversky 1979). An analysis of sentiment is necessary to further our understanding of similarities and differences in the argumentative structure of the official campaigns.

I conduct an analysis of sentiment using the R package `sentimentr`[8] (Rinker 2017), which follows a dictionary-based approach to tag polarised words. `sentimentr`

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[7] Here I assume that in dedicating disproportionate resources on a given topic, the campaign is aiming to capture voters whose voting intentions are most sensitive to that topic.

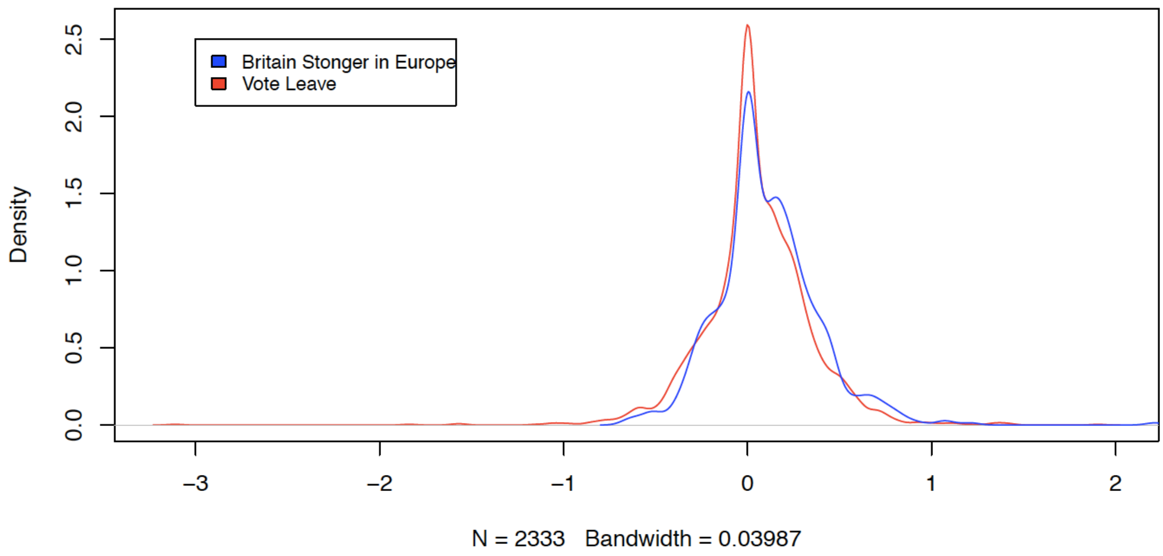
[8] Popular alternatives to the sentimentr package include syuzhet, RSentiment and Stanford. sentimentr was selected as (1) it can utilise dictionaries from alternative packages; and (2) Kawate & Patil (2017) highlights the package's balance of accuracy and speed.

attempts to take into account valence shifters (negators, amplifiers, de-amplifiers, and adversative conjunctions) while still maintaining speed. Each article is broken down into its element sentences, treated as an ordered bag of words with all punctuation removed (except for commas, colons and semicolons which are treated as words). The words in each sentence are compared to a dictionary (this analysis uses the default dictionary from the `syuzhet` package, see Jockers (2017)) that tags positive or negative words with a +1 or -1 respectively. The polarised words form a "polar cluster" which is a subset of the sentence for added context — defaulting as two words before and after a polarised word. Words in the polarised context cluster are tagged as neutral, negator, amplifier, or de-amplifier depending on their grammatical relationship to the polarised word.

The polarity score of the polarised word (i.e. +1 or -1) is acted upon by valence shifters. Identified amplifiers increase the polarity, but may become de-amplifiers if the context cluster contains an odd number of negations. Importantly, some words can act as both a [de]amplifier and a negation. Last, each sentence's weighted context clusters are summed and divided by the square root of the word count yielding an unbounded polarity score for each sentence. For more information on calculating polarity scores, see Rinker (2017). This process is conducted on all BSE and VL documents, arriving at two vectors of sentence-level polarity scores.

The kernel density estimation for the distribution of polarity scores for each website is displayed in *Figure 5*. Both follow a similar unimodal distribution centred around 0 (indicating neutral sentiment), with a small skew toward positive sentiment. The mean polarity score is 0.04914 for VL and 0.10754 for BSE.

Figure 4: Kernel Density of polarity scores



Using the list of sentiment scores for each camp, I will proceed in conducting three tests. First will be a test for the homogeneity of variance using a simple Levene's test, followed by a generalised linear model with a normally distributed error testing for the homogeneity of mean polarity score across BSE and VL's websites. For completeness, a non-parametric Kruskal-Wallis test will be conducted to provide a test for the homogeneity of median polarity score without any assumption of the underlying distribution.

To test the variability of the two samples of sentence-level polarity scores, I employed a Levene's test of homogeneity of variance. I find there to be no statistically significant difference in variance across the two campaigns (F = .21, P = .6457). This result (1) implies that the variability in sentence polarity by both campaigns were approximately equal, and (2) can justify assuming the homogeneity of variance in the following tests.

Next I use a generalised linear model (GLM) to test for differences in mean polarity score. The GLM allows a linear model to be related to the dependant variable through a link function and magnitude of the variance of each measurement to be a function of its predicted value (Nelder & Baker 1972). Using campaign affiliation as a dummy variable (V L = 0, BSE = 1), there is a statistically significant increase in polarity score from VL to BSE ($t = 4.359$, $P = 1.351 \times 10{-}5$ * * *)[9]. This shows that BSE's argumentative content tended to be more positive than its leave counterpart.

For completion, the Kruskal-Wallis test (Kruskal & Wallis 1952) is the less powerful non-parametric rank-based alternative to the one-way analysis of variance (ANOVA). This means that unlike the GLM, the Kruskal-Wallis test does not assume that errors are normally distributed. Once again we find a statistically significant difference in the two distributions ($T = 15.76$, $P = 7.209 \times 1005$ * * *) — reinforcing our findings from the GLM.

Our analysis of sentence-level polarity scores finds that (1) the variability of sentiment is equal between BSE and VL; and (2) BSE achieved significantly higher polarity scores, implying a more positive argumentative style.

7. Concluding Remarks

This paper has uncovered a number of marked differences between the two official Brexit campaigns' argumentative styles, both in the information they chose to convey, and the style in which that is conveyed. BSE's focussed approach attempted to capture voters on the most poignant issue for the electorate — the economy. Despite this, by employing a scattershot approach VL managed to target a larger subset of the total electorate – providing an avenue by which a competent campaign could put itself at an advantage. Beyond this, neither campaign appeared to address the core policies of the opposing camp, and hence a correspondence analysis uncovered little reciprocity. There was a notable exception, but by delving deeper into public services I uncovered the continuation of broader trends. Finally, while the variability of sentiment stayed constant across camp, BSE's website had a significantly greater mean sentence-level polarity score.

When interpreting these results, it is important to consider that my analysis only took place in the context of the official campaign websites. It is by no means necessarily representative of broader Brexit campaign dialogue, which could vary in a number of ways. First, stylised live debates, radio and television may differ significantly in their sentiment from website text, this could impact both the range and

[9] $P < .05$ *, $P < .01$ * *, $P < .005$ * * *

magnitude of polarity scores. Second, a number of other campaign mediums (i.e. question and answer sessions, and social media) include a degree of electorate-campaigner interaction. This would undoubtedly influence the topics emphasised in these texts, potentially emphasising those issues more important to the electorate. A larger-scale analysis of campaigning materials would be able to uncover many of these alternative trends.

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